Belief Updating and Misinformation

IFREE Presentation

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Introduction

Motivation

- Information is often not 100% reliable.
    - 37% of people reported to come across 'fake news' on a daily basis (European Commission, 2018).
    - This leads to information uncertainty more generally.

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- Uncertain information frequently gets verified.
  - A verification can lead to confirmation or retraction of previous information.
  - Both of these outcomes are common, for example in the context of scientific research during the Covid-19 pandemic.
  - At least 224 published studies on Covid-19 have been retracted since 2020 ('RetractionWatch.com').

Motivation

- It is unclear how people deal with *information about information*, i.e. verifications.
  - Some evidence that people do not fully 'unlearn' if a previous piece of information is retracted.
    - Continued influence effect - psychology literature
    - Refuted Covid-19 statements, child vaccinations and autism, deceptive mouthwash advertising[1], ...
  - It is unclear how people react to confirmations and how verifications affect future updating.

- A clear understanding of how people respond to information has important implications for the communication of policies, especially if these are based on uncertain information.

[1] Examples mentioned in Meyer et al. (2020) and Lewandowsky et al. (2012)

Literature

- Belief updating problems first studied in 60s and 70s.
  - Phillips and Edwards (1966); Kahneman and Tversky (1971,1974); and many others.
- Benjamin (2019) – Meta study
  - Strong evidence of under-inference in general.
  - No pooling of data with sequential updating.
  - Recency and primacy effect with sequential updating.
- Goncalves et al. (2021)
  - Subjects under-infer from retractions.
  - Beliefs are more sensitive to new signals after a retraction.
- Psychology literature - Continued Influence Effect[2]
  - Mechanism is based on memory and recall.
  - Works best (or mainly?) with narratives that have a causal structure.
  - Cognitive ability partly explains the size of the effect.

[2] For an overview of the literature see Ecker et al. (2022).

Research Questions

1. How do people update their belief in response to being told a previous signal was (un)informative?
   - Retraction: CIE in psychology, confirmed by Goncalves et al. (2021).
   - Confirmation: not tested. [Not part of today]

2. When do people under-react or over-react to a retraction?

3. Do verifications in the past affect inference from regular signals later on?

Experimental Design

Experimental Design

Ball and urn framework:

- 2 urns filled with different distributions of balls. One urn is randomly picked.
- Task: guess which of the urns was selected after receiving hints from the selected urn.
- Deliberately abstract design to avoid context dependencies. More

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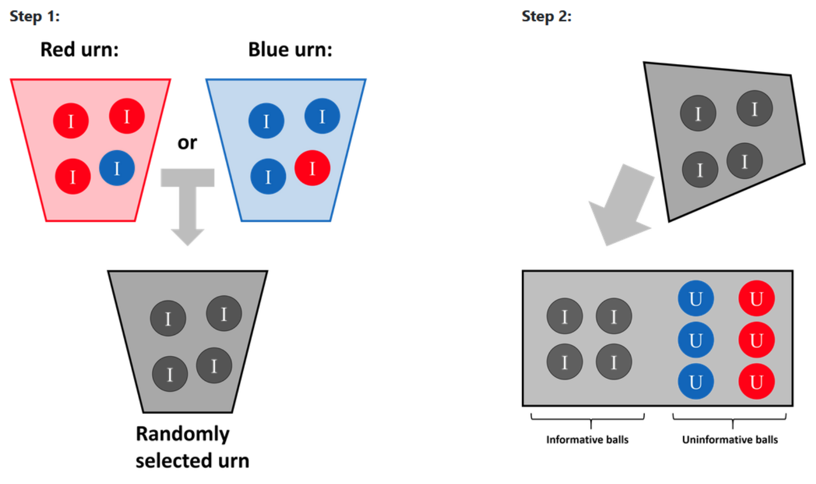
Modification:

- 4 balls from the selected urn are put into a box with 6 other, irrelevant balls, i.e. 60% chance of a signal being uninformative.
- 12 rounds of information. 9 balls are shown and 3 times information about the previous ball is displayed.
- The order of verification rounds varies per subject.

Urns and Black Box



Participant Screen

Round 7

Background:

Show/hide instructions

History:

Ball 1	Ball 2	Ball 3	Ball 4	Ball 5	Ball 6	Ball 7	Ball 8	Ball 9
?	?	?	?	U	?			

You previously thought it was **50%** likely that the selected urn is red.

New Information:

A **blue** ball was drawn from the black box: ? It is put back into the box with the other balls.

Question:

What do you think are the chances (in %) that the RED URN was picked in the beginning?

- 0 100 +

%

Implementation

- Experiment was conducted online with subjects recruited from Prolific.
- Hypotheses and analysis were pre-registered on 'aspredicted.org'.
- You can have a look at the complete experiment by visiting: `https://updatingsurvey.herokuapp.com/join/kiripame`.

Analysis

Analysis

Defining posteriors:

- Regular: Posterior is given by Bayes' rule, using the previous belief as the prior.
- Retractions: Belief before the retracted uninformative signal.
- Confirmations: Multiple options exist.

Measuring bias:

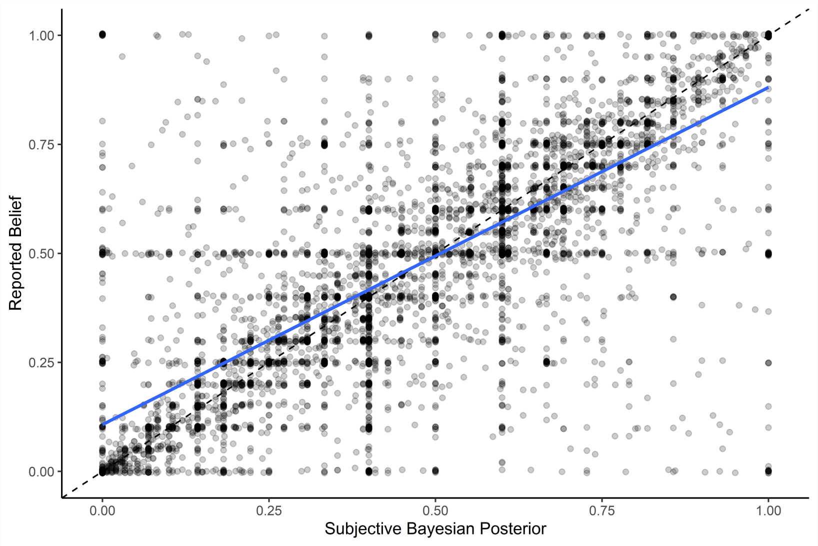
- Regular: Estimate inference and base-rate use. Method
- Retractions:
  - Estimate inference and base-rate use.
  - Average belief difference before and after retracted signal.
  - Compare compressed histories. Method
- Confirmations: Estimate inference and base-rate use.

Results

Sample Overview

- 606 subjects completed the experiment.
- 48 were removed as outliers (pre-registered criteria).
- In total 6,696 observations.
- Median time to complete survey 17 minutes.
- Average payoff is 4.80€.
- Equal ratio male/female.

Reported Beliefs vs Posteriors



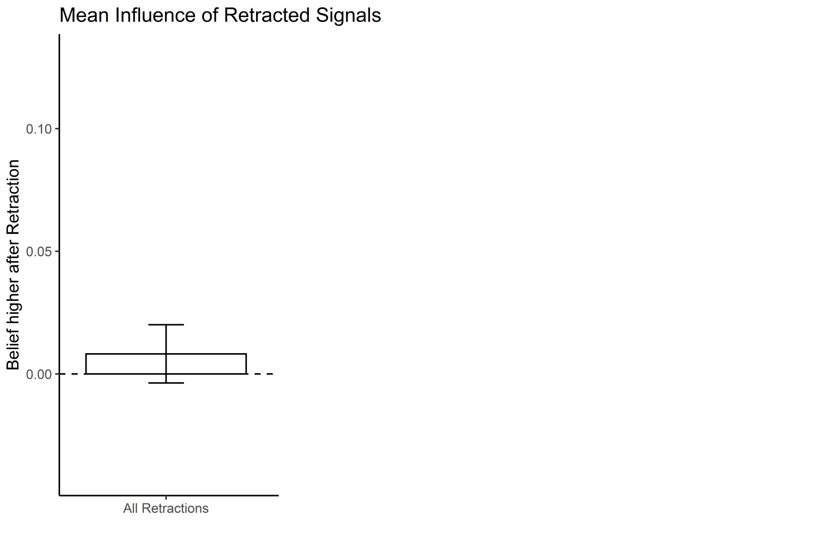
Regression

How do people react to retractions?

In general:

- No significant differences in beliefs before and after seeing an uninformative signal.
- Confirmed by analyzing compressed histories. Regression
- Contrary to Goncalves et al. (2021).

Retractions do not bias subjects on average



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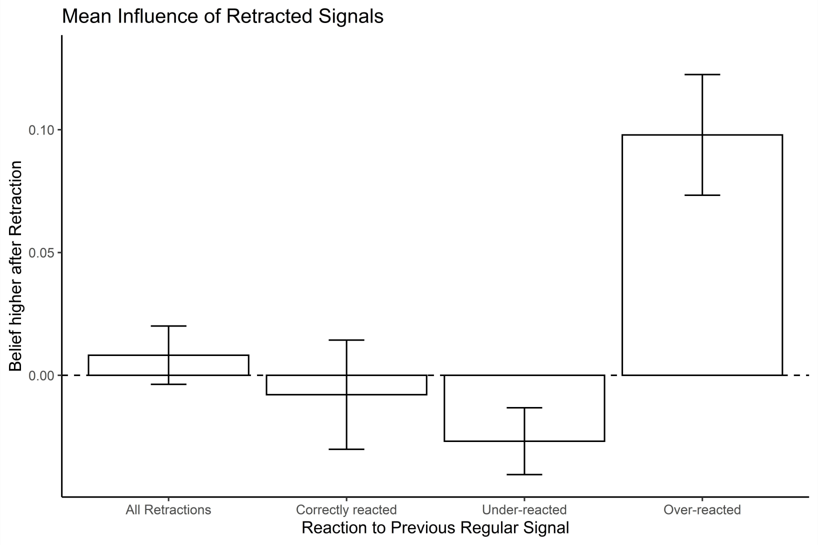
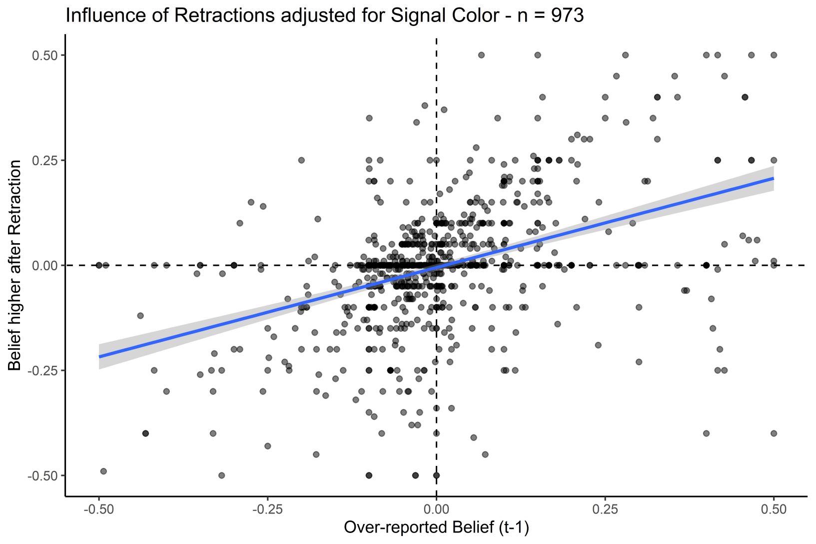
Previous update explains reaction to retractions:

- Previously over-reacted: Too high belief.
- Previously under-reacted: Too low belief.
- Previously correctly reacted: Correct belief.

Previous update explains reaction to retractions



Previous update explains reaction to retractions



Do verifications impact future regular updating?

Regular updating:

Regression

- Significant over-inference ($c \approx 1.4$).
  - Potential reason: introduction of information uncertainty.
- Significant base-rate neglect ($d \approx 0.75$).
- Evidence of confirmation bias.

Do verifications impact future regular updating?

Regular updating: Regression

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- Evidence of confirmation bias.

Impact of verifications: Regression

- No intuitively plausible finding.
- It seems that the number of past verifications of the other colored ball (retractions or confirmations) significantly decrease inference.
  - Potential reason: gambler's fallacy?

Summary

Summary

Findings:

- Updating with retractions depends on previous reaction (even in a neutral setting!)
- No continued influence on average (contrary to some earlier literature)
- Past verifications have no clear influence on future updating.

Next steps:

- Analysis of updating after confirmations.
- Investigate mechanism further?
- Influence of motivated beliefs?

Questions?

Thank you for your attention!

References

Benjamin, D. J. (2019). Errors in probabilistic reasoning and judgment biases. In *Handbook of Behavioral Economics - Foundations and Applications 2*, pages 69–186. Elsevier.

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Appendix

Why an Abstract Experimental Setting?

- An abstract setting avoids context dependencies. It seems plausible that settings with motivated beliefs would strengthen the effect.
- Our setting allows a calculation of 'correct' beliefs, using Bayes' rule. The Bayesian framework is a commonly used benchmark to estimate the inference bias.
- Retractions and confirmations of previous signals are unambiguous. In reality this is often more difficult.
- Findings can be easily compared to the broader literature on belief updating.
- Belief elicitation can be incentivized.

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Analysis: Inference and Base-Rate Use

- Use log-likelihood ratios to analyze inference bias (Benjamin, 2019).
- Estimate inference bias and base-rate neglect jointly:

$$ln\left(\frac{r_t(R|s_1,...,s_t)}{1-r_t(R|s_1,...,s_t)}\right) = \beta_0 + \beta_1 \cdot ln\left(\frac{p(s_t|R)}{p(s_t|B)}\right) + \beta_2 \cdot ln\left(\frac{r_{t-1}(R|s_1,...,s_{t-1})}{1-r_{t-1}(R|s_1,...,s_{t-1})}\right) + \eta_t$$

  - $r_t(R|s_t)$ is the reported belief of R given signals s_1 until s_t in round t.
  - $p(s|R)$ is the probability of seeing s given true state R.
- Interpretation:
  - $\beta_1 = 1$ indicates perfect Bayesian inference.
  - $\beta_1 = 0$ indicates no updating at all.
  - $\beta_2 = 1$ indicates no base-rate neglect.
  - $\beta_2 = 0$ indicates full base-rate neglect.

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Analysis: Compressed histories

- Method introduced by (Goncalves et al., 2021).
- A compressed history is given by the exact sequence of signals minus the retracted signal.
- Allows for a clean comparison between people who have seen the same sequence with and without a retraction.
- We estimate: $r_t(R|s_1, ..., s_t) = \beta_0 + \beta \cdot F_{ret_t} + F_{C(H_t)} + \eta$
  - ret_t refers to the number of seen retractions. Example: RBB would be one red retraction and 2 blue retractions in that order.
  - $C(H_t)$ refers to the compressed history of signals H_t.
  - $F(\cdot)$ denotes the fixed effects for each.
- Interpretation: A positive coefficient β for any combinations of red retracted balls indicates continued influence of retracted signals and vice versa.
- Goncalves et al. (2021) find $\beta > 0$ for a single red retraction.

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Sanity Check

OLS Regression Output

	Dependent variable:
	Reported Belief
Constant	0.111^{***}
	(0.004)
Subjective Posterior	0.765^{***}
	(0.008)
Observations	6,660
R^2	0.569
Adjusted R^2	0.569
Residual Std. Error	0.173 (df = 6658)
F Statistic	$8{,}779.675^{***}$ (df = 1; 6658)
Note:	*p<0.1; **p<0.05; ***p<0.01

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Robustness Checks - Experimental Design

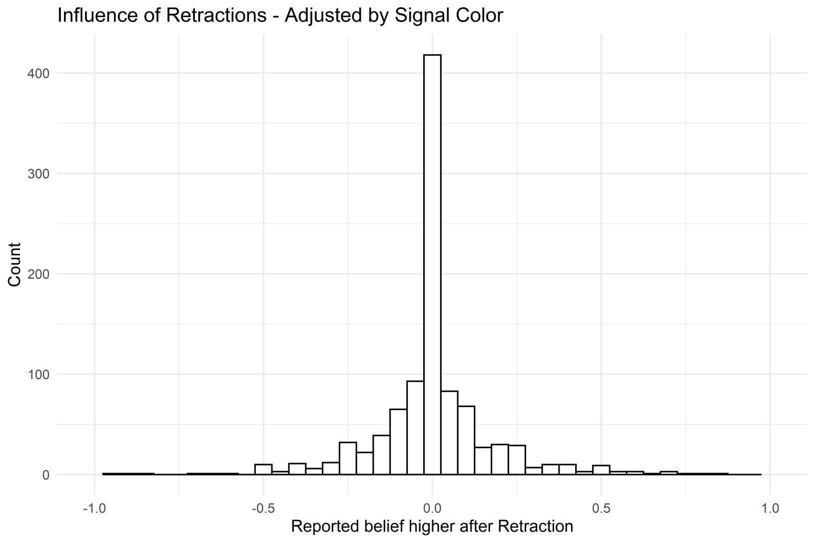
Anchoring:

- Do not show previously reported belief.
- Finding: No significant influence on updating with retractions or regular updating.
- Other: Too low belief of people that previously under-reacted no longer significant. However, not enough power to find any effect of anchoring.

Backward revision of beliefs:

- Do no show entire history of signals, only previous belief.
- Findings: No significant influence on updating with retractions or regular updating.

Impact of Retractions - Individual Differences



Impact of Retractions - Compressed History Analysis

Impact of Retractions

	Dependent variable:		
	Reported Belief		
	All histories	All histories	Excluding confirmation histories
	(1)	(2)	(3)
Retraction	-0.011	-0.008	-0.014
	(0.009)	(0.009)	(0.010)
Retraction History: R	0.006	0.003	0.005
	(0.010)	(0.011)	(0.012)
Retraction History: B	-0.003	-0.008	-0.001
	(0.009)	(0.011)	(0.012)
Retraction History: RR	0.004	-0.007	0.003
	(0.014)	(0.016)	(0.020)
Retraction History: BB	-0.017	-0.029^{*}	-0.005
	(0.013)	(0.016)	(0.018)
Retraction History: RB	0.025^{*}	0.014	0.011
	(0.014)	(0.017)	(0.020)
Retraction History: BR	0.001	-0.011	0.022
	(0.014)	(0.017)	(0.021)
Retraction History: RRR	0.053^{**}	0.035	0.054^{***}
	(0.021)	(0.025)	(0.021)
Retraction History: BBB	-0.035	-0.055^{**}	-0.033
	(0.024)	(0.028)	(0.024)
Retraction History: RRB	0.074^{*}	0.057	0.075^{*}
	(0.041)	(0.043)	(0.039)
Retraction History: BBR	0.059^{***}	0.039	0.061^{***}
	(0.023)	(0.027)	(0.022)
Retraction History: RBB	0.030	0.011	0.031
	(0.026)	(0.029)	(0.025)
Retraction History: BRR	0.043	0.023	0.045^{*}
	(0.027)	(0.030)	(0.026)
Retraction History: RBR	0.021	0.001	0.021
	(0.028)	(0.031)	(0.028)
Retraction History: BRB	0.060^{**}	0.041	0.062^{**}
	(0.030)	(0.033)	(0.029)
Compressed History FEs?	Yes	Yes	Yes
Round FEs?	No	Yes	No
Observations	6,660	6,660	3,765
Adjusted R^2	0.498	0.497	0.396
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Regular Updating - Inference and Base-Rate Use

Updating with Regular Signals

	Dependent variable:			
	Observed Log-Posterior-Ratio			
	OLS		*linear mixed-effects*	
	(1)	(2)	(3)	(4)
Constant	-0.047^{**}	-0.046^{**}	-0.039^{*}	-0.042^{*}
	(0.023)	(0.023)	(0.022)	(0.022)
Signal	1.447^{***}	1.260^{***}	1.461^{***}	1.313^{***}
	(0.059)	(0.077)	(0.062)	(0.080)
Prior	0.743^{***}	0.729^{***}	0.781^{***}	0.749^{***}
	(0.010)	(0.011)	(0.020)	(0.022)
Signal Confirms Prior		0.490^{***}		0.384^{***}
		(0.128)		(0.129)
Observations	4,995	4,995	4,995	4,995
R^2	0.539	0.540		
Adjusted R^2	0.539	0.540		
Log Likelihood			-9,103.832	-9,101.223
Akaike Inf. Crit.			18,227.660	18,224.450
Bayesian Inf. Crit.			18,292.830	18,296.120
Residual Std. Error	1.618 (df = 4992)	1.616 (df = 4991)		
F Statistic	$2{,}919.235^{***}$ (df = 2; 4992)	$1{,}956.286^{***}$ (df = 3; 4991)		

Note: *p<0.1; **p<0.05; ***p<0.01

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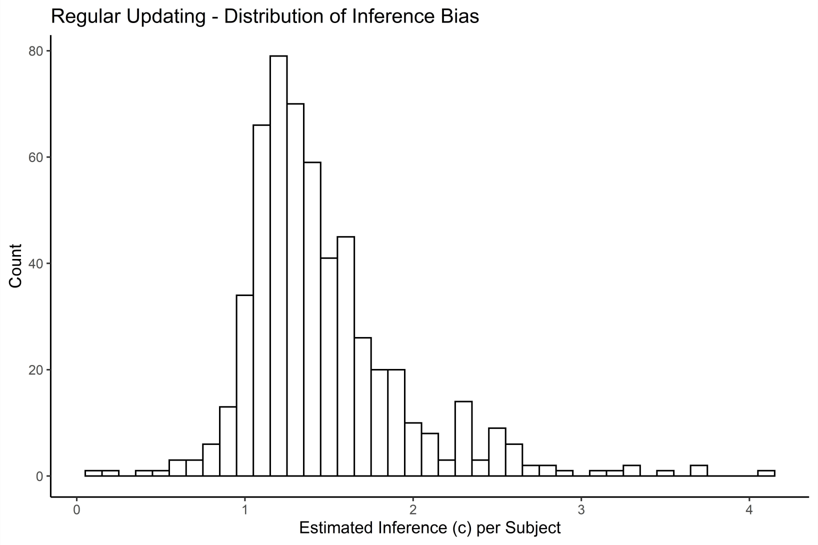
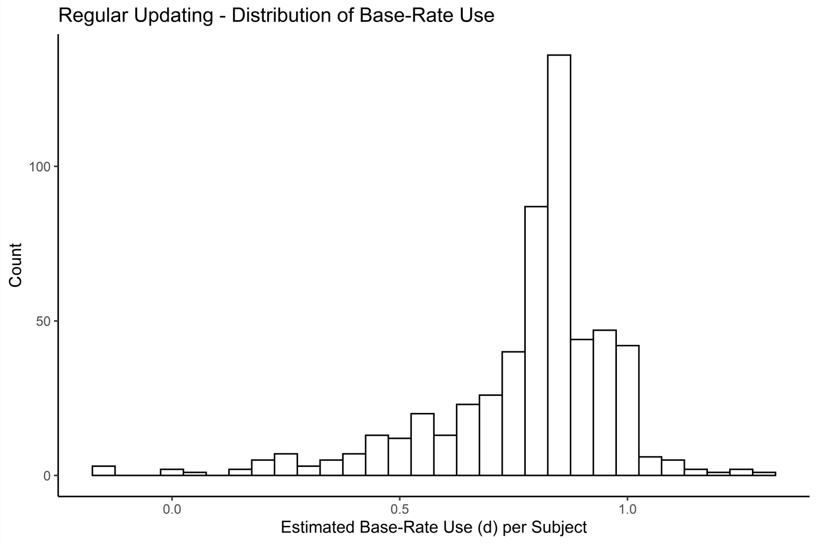
Regular Updating Types - Inference



Regular Updating Types - Base-Rate Use



Impact of Verifications on Regular Updatring

Updating with Regular Signals

	Dependent variable:		
	Observed Log-Posterior-Ratio		
	(1)	(2)	(3)
Constant	-0.046^{**}	-0.045^{**}	-0.044^{**}
	(0.022)	(0.022)	(0.022)
Signal	1.344^{***}	1.342^{***}	1.330^{***}
	(0.130)	(0.130)	(0.130)
Prior	0.919^{***}	0.920^{***}	0.905^{***}
	(0.066)	(0.066)	(0.069)
Prior * |0.5 - Prior|	-1.047^{***}	-1.048^{***}	-1.010^{***}
	(0.151)	(0.151)	(0.155)
Prior * Round	0.034^{***}	0.034^{***}	0.033^{***}
	(0.003)	(0.003)	(0.003)
Signal * Round	0.056	0.057	0.063^{*}
	(0.038)	(0.038)	(0.038)
Signal * # Previously Verified Signals	-0.182^{*}		
	(0.109)		
Signal * # Previous Retractions		-0.140	
		(0.116)	
Signal * # Previous Confirmations		-0.261^{**}	
		(0.131)	
Signal * # Previous Same Retractions			0.031
			(0.127)
Signal * # Previous Same Confirmations			-0.254
			(0.157)
Signal * # Previous Other Retractions			-0.358^{***}
			(0.132)
Signal * # Previous Other Confirmations			-0.302^{*}
			(0.161)
Observations	4,995	4,995	4,995
Log Likelihood	-9,057.651	-9,058.339	-9,055.329
Akaike Inf. Crit.	18,143.300	18,146.680	18,144.660
Bayesian Inf. Crit.	18,234.530	18,244.420	18,255.430

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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