

# Revising Beliefs in Light of Unforeseen Events

Christoph Becker <sup>1</sup>   Tigran Melkonyan <sup>2</sup>   Eugenio Proto <sup>3</sup>  
Andis Sofianos <sup>4</sup>   Stefan Trautmann <sup>1</sup>

<sup>1</sup>University of Heidelberg   <sup>2</sup>University of Alabama  
<sup>3</sup>University of Glasgow, CEPR, IZA and CESifo   <sup>4</sup>Durham University

July 30, 2025

## Unforeseen events and Bayesian updating

- ▶ Standard Bayesian paradigm is silent about how individuals react to unforeseen events
- ▶ But the universe frequently expands - observe something that was unforeseen/unforeseeable before
- ▶ Some examples: Financial crisis in 2007, Global pandemics

## Unforeseen events and Bayesian updating

- ▶ Standard Bayesian paradigm is silent about how individuals react to unforeseen events
- ▶ But the universe frequently expands - observe something that was unforeseen/unforeseeable before

## Updating in light of the unforeseen

- ▶ Consistency with prior model/beliefs
  - Reverse Bayesianism (Karni and Viero, 2013): Construction of new universe maintains consistency with old structure
  - Probability is shifted away from known outcomes proportionally  $\Rightarrow$  Keep ratios of previous estimates constant

## Unforeseen events and Bayesian updating

- ▶ Standard Bayesian paradigm is silent about how individuals react to unforeseen events
- ▶ But the universe frequently expands – observe something that was unforeseen/unforeseeable before

## Updating in light of the unforeseen

- ▶ Consistency with prior model/beliefs
  - Reverse Bayesianism (Karni and Viero, 2013): Construction of new universe maintains consistency with old structure
- ▶ Discarding, or updating towards different models
  - Agents update to new priors or models that account for the unforeseen (for example: Giacomini, et al., 2020; Ortoleva, 2012 & Ba, 2022; Lanzani, 2024)

## Unforeseen events and Bayesian updating

- ▶ Standard Bayesian paradigm is silent about how individuals react to unforeseen events
- ▶ But the universe frequently expands – observe something that was unforeseen/unforeseeable before

## Updating in light of the unforeseen

- ▶ Consistency with prior model/beliefs
  - Reverse Bayesianism (Karni and Viero, 2013): Construction of new universe maintains consistency with old structure
- ▶ Focus on rev. Bayesianism
  - Intuitively simple and directly amenable to testing
  - Rev. Bayesianism can be cogn. demanding & hindsight bias
  - Stress-test rev. Bayesianism over other models

# Main Hypotheses Tested

- H1. Participants update their beliefs according to reverse Bayesianism. That is, for any  $\hat{p}_i^o, \hat{p}_i^u$  and any outcomes  $i, i' \in C_0^F$ :

$$\frac{\hat{p}_i^o}{\hat{p}_{i'}^o} = \frac{\hat{p}_i^u}{\hat{p}_{i'}^u}$$

- H2. Participants do not anticipate unforeseen consequences, i.e, the residual estimate:  $\hat{p}_x = 0$
- H3. Participants will not adjust their residual belief after an unforeseen event:  $\hat{p}_x^u - \hat{p}_x^o = 0$

# Overview of Experiments

## Experiment 1

- ▶ Observe random draws from urn, then provide estimates.
- ▶ Elicits implicit residual probabilities.

## Experiment 3

- ▶ Stress-test rev. Bayesianism when regime change is possible

## Experiment 2

- ▶ Explore urn sequentially, providing estimates after each draw.
- ▶ Elicits explicit residual probabilities.

# General Design of Experiment 1

1. Observe 20 physical draws from a real urn
  - *Original* urn: 24 balls worth 80 and 36 balls worth 190

# General Design of Experiment 1

1. Observe 20 physical draws from a real urn
  - *Original* urn: 24 balls worth 80 and 36 balls worth 190
2. After observing draws:
  - Report probabilities:  $\hat{p}_{80}^o, \hat{p}_{190}^o$  (Karni method [▶ Details](#))
  - Do not need to add up to 1  $\implies \hat{p}_x^o = 1 - \hat{p}_{80}^o - \hat{p}_{190}^o$
  - Report valuation of urn through:  $WTA^o$  (BDM [▶ Details](#))

# General Design of Experiment 1

1. Observe 20 physical draws from a real urn
  - *Original* urn: 24 balls worth 80 and 36 balls worth 190
2. After observing draws:
  - Report probabilities:  $\hat{p}_{80}^o, \hat{p}_{190}^o$  (Karni method [▶ Details](#))
  - Do not need to add up to 1  $\implies \hat{p}_x^o = 1 - \hat{p}_{80}^o - \hat{p}_{190}^o$
  - Report valuation of urn through:  $WTA^o$  (BDM [▶ Details](#))
3. Previously hidden *new* urn is revealed and its content emptied into original urn  $\rightarrow$  *Updated* urn
  - *New* urn: 15 balls either worth 15 or 375 (depending on condition)

# General Design of Experiment 1

1. Observe 20 physical draws from a real urn
  - *Original* urn: 24 balls worth 80 and 36 balls worth 190
2. After observing draws:
  - Report probabilities:  $\hat{p}_{80}^o, \hat{p}_{190}^o$  (Karni method [▶ Details](#))
  - Do not need to add up to 1  $\implies \hat{p}_x^o = 1 - \hat{p}_{80}^o - \hat{p}_{190}^o$
  - Report valuation of urn through:  $WTA^o$  (BDM [▶ Details](#))
3. Previously hidden *new* urn is revealed and its content emptied into original urn  $\rightarrow$  *Updated* urn
  - *New* urn: 15 balls either worth 15 or 375 (depending on condition)
4. Participants now report:  $\hat{p}_{80}^u, \hat{p}_{190}^u, \hat{p}_S^u$ , and  $WTA^u$  (Karni method & BDM)

# General Design of Experiment 1

1. Observe 20 physical draws from a real urn
  - *Original* urn: 24 balls worth 80 and 36 balls worth 190
2. After observing draws:
  - Report probabilities:  $\hat{p}_{80}^o, \hat{p}_{190}^o$  (Karni method [▶ Details](#))
  - Do not need to add up to 1  $\implies \hat{p}_x^o = 1 - \hat{p}_{80}^o - \hat{p}_{190}^o$
  - Report valuation of urn through:  $WTA^o$  (BDM [▶ Details](#))
3. Previously hidden *new* urn is revealed and its content emptied into original urn  $\rightarrow$  *Updated* urn
  - *New* urn: 15 balls either worth 15 or 375 (depending on condition)
4. Participants now report:  $\hat{p}_{80}^u, \hat{p}_{190}^u, \hat{p}_S^u$ , and  $WTA^u$  (Karni method & BDM)

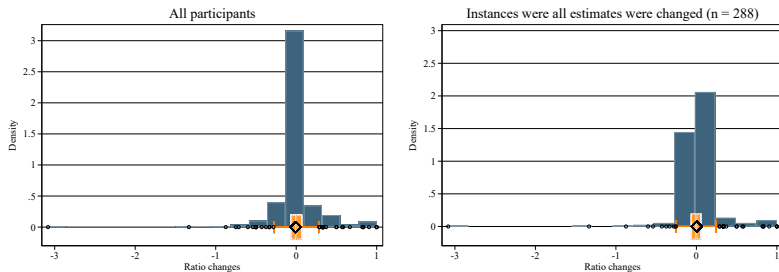
Two conditions: Information Surprise & Payment Surprise [▶ Timeline](#)

- Students from University of Heidelberg and KIT
- 344 participants in total
- The design was pre-registered at the AEA RCT Registry

# Reverse Bayesianism

Histograms of the ratio changes before vs. after the urn is updated

$$\Delta R = \frac{\hat{p}_{80}^o}{\hat{p}_{190}^o} - \frac{\hat{p}_{80}^u}{\hat{p}_{190}^u}$$



Histogram in blue, box plot in orange, outliers (circles) and mean (diamond) in black.

- ▶ Participants consistent with rev. Bayesianism. [▶ Statistical Tests](#)
- ▶ Ratios remain constant, but individual estimates *are* updated. [▶ Evidence](#)
- [▶ Residuals](#)

# Overview of Experiments

## Experiment 1

- ▶ Observe random draws from urn, then provide estimates.
- ▶ Elicits implicit residual probabilities.

## Experiment 3

- ▶ Stress-test rev. Bayesianism when paradigm shift is possible

## Experiment 2

- ▶ Explore urn sequentially, providing estimates after each draw.
- ▶ Elicits explicit residual probabilities.

## Experiment 2 - Design

Participants draw 30 samples out of 4 different virtual urns containing different colours (100 marbles per urn).

- ▶ Draws and colours are randomized [▶ Example screen](#)
- ▶ After each draw (Karni method):
  - State probability estimate for every observed outcome so far.
  - State a probability estimate for the residual,  $\hat{p}_x$ .

	Task 1		Task 2	Task 3	Task 4
	Two colours	Four colours			
Colour 1	55	40	53	75	48
Colour 2	45	28	35	25	28
Colour 3		20	12		12
Colour 4		12			12

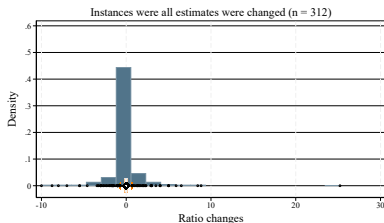
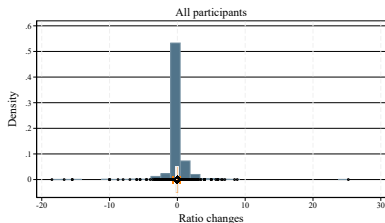
- Students from Warwick Business School
- 174 participants in total
- The design was pre-registered at the AEA RCT Registry

# Reverse Bayesianism

Histograms of ratio changes before vs. after the urn is updated

$$\text{Third outcome: } \Delta R^3 = \frac{\hat{p}_H^U}{\hat{p}_L^U} - \frac{\hat{p}_H^O}{\hat{p}_L^O}$$

$$\text{Fourth outcome: } \Delta R_1^4 = \frac{\hat{p}_H^U}{\hat{p}_M^U} - \frac{\hat{p}_H^O}{\hat{p}_M^O}; \Delta R_2^4 = \frac{\hat{p}_M^U}{\hat{p}_L^U} - \frac{\hat{p}_M^O}{\hat{p}_L^O}; \Delta R_3^4 = \frac{\hat{p}_H^U}{\hat{p}_L^U} - \frac{\hat{p}_H^O}{\hat{p}_L^O}$$



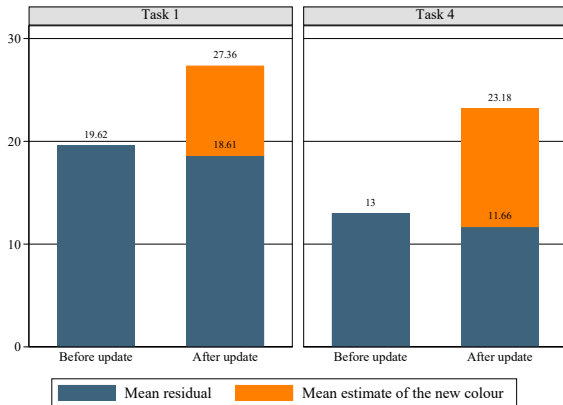
Histogram in blue, box plot in orange, outliers (circles) and mean (diamond) in black.

Again:

- ▶ Participants consistent with rev. Bayesianism. [▶ Statistical Tests](#)
- ▶ Ratios remain constant, but individual estimates *are* updated. [▶ Evidence](#)

# To what degree are participants Bayesian updaters?

- Unpacking bias (Tversky and Koehler, 1994; Sonnemann et al., 2013)



► Other graphs

- Unpacked estimate is significantly larger than the original residual ( $p$  – values < 0.001, both before and after correction)

## Exp. 3: Design

- ▶ Similar to exp. 2:
  - 40 samples from 3 different virtual urns (with replacement)
  - Each urn contains 3 outcomes with a total of 100 marbles
    - \* Participants do not know number of outcomes or proportions
  - After each sampling round, participants report (Karni method):
    - \* Probability estimate for every observed color so far
    - \* Probability estimate for 'yet unobserved' colors

## Exp. 3: Design

- ▶ Similar to exp. 2:
  - 40 samples from 3 different virtual urns (with replacement)
  - Each urn contains 3 outcomes with a total of 100 marbles
    - \* Participants do not know number of outcomes or proportions
  - After each sampling round, participants report (Karni method):
    - \* Probability estimate for every observed color so far
    - \* Probability estimate for 'yet unobserved' colors
- ▶ Participants informed that after some point the urn might be completely replaced
  - Replacement urn always has 5 different outcomes with equal proportion

## Exp. 3: Design

- ▶ Similar to exp. 2:
  - 40 samples from 3 different virtual urns (with replacement)
  - Each urn contains 3 outcomes with a total of 100 marbles
    - \* Participants do not know number of outcomes or proportions
  - After each sampling round, participants report (Karni method):
    - \* Probability estimate for every observed color so far
    - \* Probability estimate for 'yet unobserved' colors
- ▶ Participants informed that after some point the urn might be completely replaced
  - Replacement urn always has 5 different outcomes with equal proportion
- ▶ Two treatments:
  1. Announcement treatment
  2. Full Information treatment

## Exp. 3: Rev. Bayesianism

	Obs	Avg ratio change	p-value	Num significant individual tests	95%CI	Bayes factor
Before regime change possible						
$\Delta R^3$	615	-0.19	0.762	0 (3)	[-0.54, 0.15]	12.13
After regime change possible						
$\Delta R^3$ <i>Announcement</i>	45	0.05	0.342	0 (2) <sup>†</sup>	[-0.49, 0.6]	6.33
$\Delta R^3$ <i>Full information</i>	57	-0.59	0.058	1 (2) <sup>†</sup>	[-1.14, -0.03]	1.03
$\Delta R^4$ <i>Announcement</i>	937	-0.07	0.000	3 (9)	[-0.26, 0.13]	22.75
$\Delta R^4$ <i>Full information</i>	974	-1.10	0.000	8 (9)	[-1.39, -0.82]	0
$\Delta R^5$ <i>Announcement</i>	1,181	-0.38	0.000	6 (18)	[-0.57, -0.19]	0.03
$\Delta R^5$ <i>Full information</i>	1,263	-0.66	0.000	11 (18)	[-0.87, -0.45]	0

Wilcoxon signed-rank test, confidence interval from one sample t-test, Bayes factor from JZS test. 'Num. individual significant tests' refers to how many out of each individual tests are found to be significant before correcting for multiple hypotheses testing (total number of tests in parentheses).<sup>†</sup> Since every participant in Task 30 encountered the third color before the regime change, a third individual test was not possible.

- ▶ Participants consistent with rev. Bayesianism before a regime change is possible
- ▶ After regime change is possible, abandon rev. Bayesianism
  - Clearer and stronger effect in full information treatment

## Exp. 3: Rev. Bayesianism

Subjects with constant  $\Delta R^3$  before regime change possible

	Obs	Avg ratio change	p-value	Num significant individual tests	95%CI	Bayes factor
$\Delta R^4$ <i>Announcement</i>	394	0.23	0.001	1 (9)	[-0.01, 0.46]	5.82
$\Delta R^4$ <i>Full information</i>	420	-0.83	0.000	7 (9)	[-1.14, -0.53]	0
$\Delta R^5$ <i>Announcement</i>	512	-0.47	0.001	0 (18)	[-0.75, -0.19]	0.24
$\Delta R^5$ <i>Full information</i>	520	-0.77	0.000	2 (18)	[-1.1, -0.45]	0

Wilcoxon signed-rank test, confidence interval from one sample t-test, Bayes factor from JZS test. 'Num. individual significant tests' refers to how many out of each individual tests are found to be significant before correcting for multiple hypotheses testing (total number of tests in parentheses).

- ▶ These perfect rev. Bayesians also abandon rev. Bayesianism – not individual characteristic, rather context/environment dependent

## Concluding remarks

- ▶ We find that behaviour conforms with rev. Bayesianism
  - Holds whether participants did or not expect further surprises
    - ▶ Evidence-Exp1
    - ▶ Evidence-Exp2
  - Despite other biases in beliefs (unpacking of estimates after surprise)
- ▶ Faced with environment change possibility, behaviour does not conform with rev. Bayesianism especially if offered information on new world order
- ▶ Rev. Bayesianism seems to be less a characteristic of the DM and more depending on the situation/context

Thanks for your attention

## Karni (2009) Method

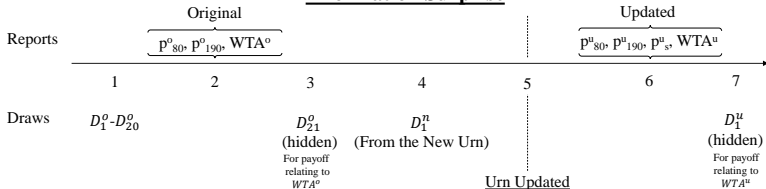
- ▶ Participants are asked to express a perceived likelihood or probability for a prize – in our case, proportion of prizes equal to value  $X$  within the urn
- ▶ This declared probability is compared to a random number between 0 and 1
- ▶ **IF** the random number is greater than the declared probability, participants receive a lottery paying  $X$  according to the true proportion of prize  $X$  within the urn
- ▶ Instead, **IF** the random number is less than the declared probability, participants receive a lottery paying  $X$  according to the random number probability
- ▶ Participants were told that declaring their true perception is in their best interest, if interested in more details they could click on a button explaining the above procedure

# Standard BDM Method

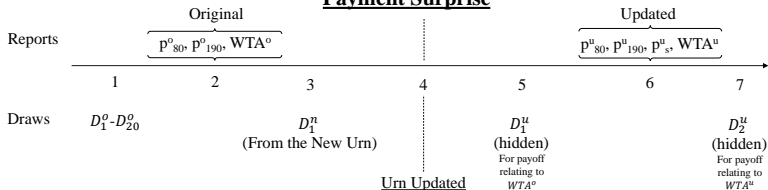
## Some details

- ▶ This method asks participants to state a minimum willingness to accept (WTA) for an item – in our context a lottery
- ▶ Their stated value is then compared to a random number
- ▶ **IF** stated WTA is greater than the random number, the participant does not sell the lottery and will thus be paid according to the realisation of the lottery
- ▶ Instead, **IF** stated WTA is less than or equal to the random number, the participant gets to sell the lottery for *the value of the random number*
- ▶ BDM method is said to be incentive compatible, i.e. aligns incentives for truthful reporting

## Information Surprise



## Payment Surprise



(*o* – original urn; *n* – new urn; *u* – updated urn)

▶ IS Details

▶ PS Details

▶ Treatment Reasoning

▶ Back to Design Overview

## Exp. 1 Design: Information Surprise (IS) Condition

1. Original urn:
  - Participants told: *"the urn contains two and only two prizes"*.
  - Not told what these prizes or their relative proportions are.
  - **Not** alerted on possible changes to composition of urn.
2. After reports on original urn:
  - Hidden draw relating to  $WTA^o$ .
3. New  $\Rightarrow$  Updated urn:
  - Draw one ball from new urn and told: *"This urn contains only the prize you are (about to be) shown"*.
4. After reports on updated urn:
  - Hidden draw relating to  $WTA^u$ .

## Exp. 1 Design: Payment Surprise (PS) Condition

### 1. Original urn:

- Participants told: *“new balls representing different tokens to what you have been observing so far may be added to this urn”*.
- Not told about number of prizes in urn or anything about proportion of any prize.

### 2. New $\Rightarrow$ Updated urn:

- Draw one ball from new urn and told: *“This urn contains new prizes. One such prize is the one you see. The urn contains no prizes similar to what you have been observing as a result of random draws from the other urn”*.

### 3. After urn is updated:

- Hidden draw relating to  $WTA^o$ .

### 4. After reports on updated urn:

- Hidden draw relating to  $WTA^u$ .

## Contrasting IS with PS condition

- ▶ Our aim is to induce an unforeseeable event and study reactions to it
- ▶ For an event to be unforeseeable it must:
  1. be unannounced and/or ruled out
  2. have immediate payment consequences
- ▶ Incorporating both risks a design that would contain deception
  - either by ruling out any new event and then enforcing a payment relevant surprise
  - or by enforcing a payment relevant surprise without forewarning
- ▶ Hence, two conditions:
  - IS: New event unannounced, but not instantly payment-relevant
  - PS: New event instantly payment-relevant, but forewarned

# Reverse Bayesianism

## Statistical tests

$$\Delta R = \frac{\hat{P}_{80}^o}{\hat{P}_{190}^o} - \frac{\hat{P}_{80}^u}{\hat{P}_{190}^u} = 0$$

		Obs	Avg ratio change	p-value	p-value (corr)	95%CI	Bayes factor
IS	low prize	75	0.007	0.375	0.981	[-0.05, 0.06]	7.61
	high prize	75	-0.039	0.981	0.981	[-0.14, 0.06]	5.88
PS	low prize	93	0.016	0.918	0.981	[-0.03, 0.06]	6.83
	high prize	100	-0.007	0.011	0.043	[-0.05, 0.03]	8.56

Wilcoxon signed-rank test, confidence interval from one sample t-test Bayes factor from JZS test, p-values corrected by Benjamini-Hochberg method.

		Increased	Decreased	Const ratio	Unchanged Est
IS	low prize	29	23	23	1
	high prize	31	32	12	1
PS	low prize	33	37	23	0
	high prize	29	61	10	4

'Unchanged Est' denotes the subset of those holding their ratios constant while not changing any of their estimates.

## Participants consistent with rev. Bayesianism, supporting $H1$

[▶ Back](#)

# Do estimates of known outcomes change?

Ratios remain constant, but individual estimates *are* updated

		Obs	Diff	p-value	p-value (corr)
IS, low prize	$\hat{p}_{80}^u - \hat{p}_{80}^o$	76	-0.101	0.000	0.000
	$\hat{p}_{190}^u - \hat{p}_{190}^o$	76	-0.130	0.000	0.000
IS, high prize	$\hat{p}_{80}^u - \hat{p}_{80}^o$	75	-0.102	0.000	0.000
	$\hat{p}_{190}^u - \hat{p}_{190}^o$	75	-0.125	0.000	0.000
PS, low prize	$\hat{p}_{80}^u - \hat{p}_{80}^o$	93	-0.100	0.000	0.000
	$\hat{p}_{190}^u - \hat{p}_{190}^o$	93	-0.136	0.000	0.000
PS, high prize	$\hat{p}_{80}^u - \hat{p}_{80}^o$	100	-0.075	0.000	0.000
	$\hat{p}_{190}^u - \hat{p}_{190}^o$	100	-0.108	0.000	0.000

Wilcoxon signed-rank test, p-values corrected by Benjamini-Hochberg procedure.

# Residuals

## Results for H2:

- ▶  $\hat{\rho}_x^o = 0$  cannot be rejected in any treatment  $\Rightarrow$  People do not implicitly expect the unknown
- ▶  $\hat{\rho}_x^u = 0$  rejected in the PS, low prize treatment. [▶ Statistical Tests](#)
- ▶ Generally support for  $H2$

## Results for H3:

- ▶ Overall,  $\hat{\rho}_x^u - \hat{\rho}_x^o = 0$  in most treatments.
- ▶ Some evidence of  $\hat{\rho}_x^u \neq \hat{\rho}_x^o$  in (PS, low prize). [▶ Statistical Tests](#)
- ▶ In line with  $H3$ .

[▶ Back](#)

## Residuals different from zero

		$\hat{\rho}_x^t = 0$	$\hat{\rho}_x^t > 0$	$\hat{\rho}_x^t < 0$	p-value	p-value (corr)
IS, original	low prize	74	1	1	0.993	0.993
	high prize	71	3	1	0.314	0.952
PS, original	low prize	92	0	1	0.317	0.952
	high prize	90	6	4	0.549	0.993
IS, updated	low prize	61	10	5	0.251	0.952
	high prize	65	7	3	0.228	0.952
PS, updated	low prize	74	16	3	0.004	0.028
	high prize	84	11	5	0.146	0.952

Wilcoxon signed-rank test, p-values corrected by Benjamini-Hochberg procedure.

- ▶  $\hat{\rho}_x^o = 0$  cannot be rejected in any treatment  $\Rightarrow$  People do not implicitly expect the unknown
- ▶  $\hat{\rho}_x^u = 0$  rejected in the PS, low prize treatment
- ▶ Generally support for  $H_2$

## Adjusting beliefs after an unforeseen event

$$\Delta \hat{p}_x = \hat{p}_x^u - \hat{p}_x^o = 0$$

		$\Delta \hat{p}_x = 0$	$\Delta \hat{p}_x > 0$	$\Delta \hat{p}_x < 0$	p-value	p-value (corr)
IS	low prize	60	11	5	0.173	0.519
	high prize	63	6	6	0.937	0.937
PS	low prize	73	17	3	0.002	0.009
	high prize	82	11	7	0.345	0.690

Wilcoxon signed-rank test, p-values corrected by Benjamini-Hochberg procedure.

- ▶ Overall, support for  $H3$
- ▶ Some evidence of  $\hat{p}_x^u \neq \hat{p}_x^o$  in  $(PS, \text{low prize})$

# Part 1

Please draw a sample from the box.

Sample draw: 30



**maroon**

Please indicate in the fields below, how many marbles of a samples color you think are in this box. Remember, the box has a total of 100 marbles.

Number of <b>orange</b> marbles:	<input type="text"/>	Fill previous estimate	+	-
Number of <b>maroon</b> marbles:	<input type="text"/>	Fill previous estimate	+	-
Number of <b>blue</b> marbles:	<input type="text"/>	Fill previous estimate	+	-
Number of <b>salmon</b> marbles:	<input type="text"/>	Fill previous estimate	+	-
Number of marbles of <b>any other color</b> :	<input type="text"/>	Fill previous estimate	+	-



Go to part 2

▶ Back

## Exp. 2: Reverse Bayesianism

Statistical tests: Participants consistent with rev. Bayesianism

$$\text{Third outcome: } \Delta R^3 = \frac{\hat{\rho}_H^u}{\hat{\rho}_L^u} - \frac{\hat{\rho}_H^o}{\hat{\rho}_L^o} = 0$$

$$\text{Fourth outcome: } \Delta R_1^4 = \frac{\hat{\rho}_H^u}{\hat{\rho}_M^u} - \frac{\hat{\rho}_H^o}{\hat{\rho}_M^o} = 0; \Delta R_2^4 = \frac{\hat{\rho}_M^u}{\hat{\rho}_L^u} - \frac{\hat{\rho}_M^o}{\hat{\rho}_L^o} = 0; \Delta R_3^4 = \frac{\hat{\rho}_H^u}{\hat{\rho}_L^u} - \frac{\hat{\rho}_H^o}{\hat{\rho}_L^o} = 0$$

	Obs	Avg ratio change	p-value	Num individual significant tests	95%CI	Bayes factor
$\Delta R^3$	427	-0.081	0.010	1 (3)	[-0.18, 0.02]	5.15
$\Delta R^4$	742	-0.024	0.154	1 (6)	[-0.18, 0.13]	23.14

Wilcoxon signed-rank test, confidence interval from one sample t-test, Bayes factor from JZS test. 'Num. individual significant tests' refers to how many out of each individual tests are found to be significant before correcting for multiple hypotheses testing (total number of tests in parentheses)

▶ Ind. Tests

▶ Ratio changes tests

▶ Known outcome estimates tests

▶ Back

## Exp. 2: Reverse Bayesianism

Individual statistical tests: Participants consistent with rev. Bayesianism

$$\text{Third outcome: } \Delta R^3 = \frac{\hat{p}_H^u}{\hat{p}_L^u} - \frac{\hat{p}_H^o}{\hat{p}_L^o} = 0$$

$$\text{Fourth outcome: } \Delta R_1^4 = \frac{\hat{p}_H^u}{\hat{p}_M^u} - \frac{\hat{p}_H^o}{\hat{p}_M^o} = 0; \Delta R_2^4 = \frac{\hat{p}_M^u}{\hat{p}_L^u} - \frac{\hat{p}_M^o}{\hat{p}_L^o} = 0; \Delta R_3^4 = \frac{\hat{p}_H^u}{\hat{p}_L^u} - \frac{\hat{p}_H^o}{\hat{p}_L^o} = 0$$

		Obs	Avg ratio change	p-value	p-value (corr)	95%CI	Bayes factor
Task 1	$\Delta R^3$	85	0.10	0.172	0.962	[-0.1, 0.29]	5.32
	$\Delta R_1^4$	84	-0.29	0.584	0.962	[-0.79, 0.21]	4.44
	$\Delta R_2^4$	84	-0.62	0.033	0.263	[-1.27, 0.03]	1.58
	$\Delta R_3^4$	84	-0.10	0.315	0.962	[-0.52, 0.32]	7.52
Task 2	$\Delta R^3$	169	-0.15	0.008	0.076	[-0.31, 0.01]	2.26
Task 4	$\Delta R^3$	173	-0.10	0.517	0.962	[-0.26, 0.06]	5.71
	$\Delta R_1^4$	164	0.09	0.962	0.962	[-0.06, 0.25]	6.05
	$\Delta R_2^4$	163	0.25	0.946	0.962	[-0.18, 0.69]	6.09
	$\Delta R_3^4$	163	0.06	0.883	0.962	[-0.14, 0.27]	9.46

Wilcoxon signed-rank test, confidence interval from one sample t-test, Bayes factor from JZS test, p-values corrected by Benjamini-Hochberg procedure.

## Exp. 2: Reverse Bayesianism

### Statistical tests II

	Increased	Decreased	Const ratio	Unchanged Est
$\Delta R^3$	96	138	193	117
$\Delta R^4$	198	239	305	147

- ▶ Many keep estimates unchanged; possibly due to re-fill button
- ▶ Substantial share holds ratio constant, not trivial especially after fourth outcome

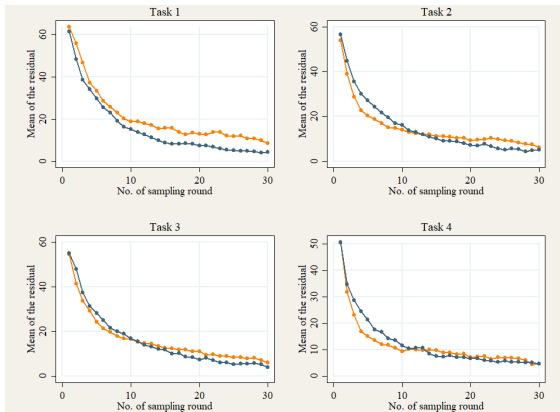
▶ Back

# Do estimates of known outcomes change?

		Obs	Diff	p-value	p-value (corr)
Task 1, after third color	$\hat{\rho}_H^u - \hat{\rho}_H^o$	85	-0.06	0.000	0.000
	$\hat{\rho}_L^u - \hat{\rho}_L^o$	85	-0.04	0.000	0.000
Task 1, after fourth color	$\hat{\rho}_H^u - \hat{\rho}_H^o$	84	-0.05	0.000	0.000
	$\hat{\rho}_M^u - \hat{\rho}_M^o$	84	-0.02	0.000	0.000
	$\hat{\rho}_L^u - \hat{\rho}_L^o$	84	-0.01	0.019	0.019
Task 2, after third color	$\hat{\rho}_H^u - \hat{\rho}_H^o$	169	-0.08	0.000	0.000
	$\hat{\rho}_L^u - \hat{\rho}_L^o$	169	-0.04	0.000	0.000
Task 4, after third color	$\hat{\rho}_H^u - \hat{\rho}_H^o$	174	-0.09	0.000	0.000
	$\hat{\rho}_L^u - \hat{\rho}_L^o$	174	-0.05	0.000	0.000
Task 4, after fourth color	$\hat{\rho}_H^u - \hat{\rho}_H^o$	164	-0.05	0.000	0.000
	$\hat{\rho}_M^u - \hat{\rho}_M^o$	164	-0.03	0.000	0.000
	$\hat{\rho}_L^u - \hat{\rho}_L^o$	164	-0.02	0.000	0.000

Wilcoxon signed-rank test, p-values corrected by Benjamini-Hochberg procedure.

# Dynamics of Residuals

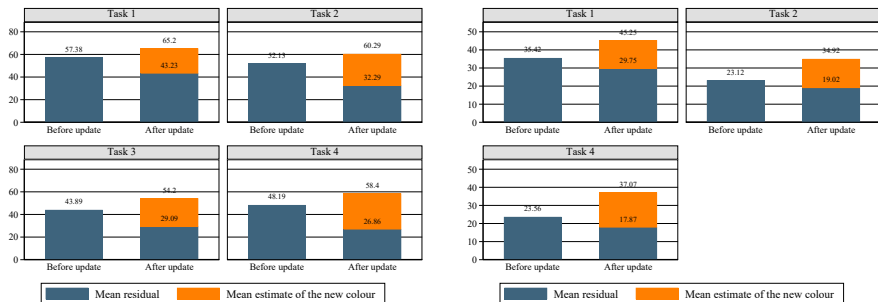


▶ Back

- ▶ No difference between treatments (Kolmogorov-Smirnov test, all  $p$  - values  $> 0.994$ ).
- ▶ Pearson correlation coefficient between # of samples and  $\hat{\rho}_x$ :  $\rho < -0.311$
- ▶ Spearman correlation coefficient between # of observed colours and  $\hat{\rho}_x$ :  $\rho < -0.272$

# To what degree are participants Bayesian updaters?

After second & third colour discovery



▶ Back

## Exp. 3: Implementation

- ▶ Replacement can occur:
  - After 30th draw for first urn
  - After 20th draw for second urn
  - After 10th draw for third urn
- ▶ Participants could earn 7 EUR or nothing from each task depending on the Karni method
- ▶ All sessions completed with short Raven test for cognitive ability and general demographics questionnaire
- ▶ Sessions at University of Heidelberg
- ▶ Software: Otree
- ▶ Average earnings: 15.98 EUR
- ▶ 241 participants across the two treatments
- ▶ The design was pre-registered at the AEA RCT Registry  
<https://doi.org/10.1257/rct.12369-4.0>

## Exp. 3: Ratio changes before vs. after observing new colour

	Increased	Decreased	Constant	Unchanged Est
Before regime change possible				
$\Delta R^3$	148	154	313	201
After regime change possible				
$\Delta R^3$ <i>Announcement</i>	13	19	13	9
$\Delta R^3$ <i>Full information</i>	16	29	12	11
$\Delta R^4$ <i>Announcement</i>	244	393	300	159
$\Delta R^4$ <i>Full information</i>	180	477	317	201
$\Delta R^5$ <i>Announcement</i>	280	429	472	180
$\Delta R^5$ <i>Full information</i>	167	391	705	576

► Back