“Do We Follow Others when We Should?
A Simple Test of Rational Expectations”: Comment

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Online Appendix

Appendix A describes the new meta-dataset of information cascade experiments that we compiled and it provides a classification of the included experimental treatments. Appendix B presents a general class of information cascade games which encompasses all the experimental settings included in the new meta-dataset. Appendix C provides the intermediate steps of the decomposition of the empirical payoff of actions for this general class of games. Appendices D and E complement the statistical analyses discussed in the main text. Appendix F reports on two simulation studies which illustrate the relative contribution of sampling errors in choice probabilities and information parameters to the errors-in-variables problem in tests of rational expectations.

Appendix A. Meta-Datasets of Information Cascade Experiments

This appendix first details the differences between the meta-dataset presented in Weizsäcker (2010)[1] and the new meta-dataset that we compiled (henceforth the W and the ZMK meta-dataset, respectively). The second section of Appendix A provides a classification of the experimental treatments included in the ZMK meta-dataset.

A.1. Differences between the W and the ZMK Meta-Datasets

The ZMK meta-dataset has been obtained by modifying the W meta-dataset in three different ways. First, we corrected some mismatches between the data included in the W meta-dataset and the original data, and we made cosmetic changes in an attempt to increase the usability of the meta-dataset. Second, we excluded 510 decisions from two pilot sessions and one interrupted session in Dominitz and Hung (2009). We also excluded the 36 decisions from the last repetition of each session in Oberhammer and Stiehler (2003). Third, we included all 1,440 decisions from Ziegelmeyer, Koessler, Bracht, and Winter (2010) as well as the 1,080 decisions made by individuals in the experimental condition *private information* of Fahr and Irlenbusch (2011). The ZMK meta-dataset contains a total of 31,086 decisions made by 3,000 participants in 14 information cascade experiments.

We detail below the major differences, when they exist, between the two meta-datasets for each data source.[2] Unless specified otherwise, the labels and values of the variables are those of the ZMK meta-dataset and labels are enclosed by quotation marks.

A.1.1. Anderson and Holt (1997)

Both the W and the ZMK meta-datasets contain 810 decisions from two experimental conditions of the data source, the experimental condition with *asymmetric design* and the experimental condition with *symmetric design* (without public draws).[3] The ZMK meta-dataset indicates 3 and 6 sessions with one group of participants each for the experimental condition "Asymmetric" and "Symmetric", respectively (as opposed to one session with 3 and 6 groups in the W meta-dataset). We also adjusted the signal quality for the experimental condition "Symmetric" to 2/3 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.2. Willinger and Ziegelmeyer (1998)

Both the W and the ZMK meta-datasets include the 324 decisions from *treatment 1* of the data source.[4] The ZMK meta-dataset indicates 6 sessions with one group of participants each (as opposed to one session with 6 groups in the W meta-dataset). We corrected 102 mismatched values of the variable "State" which records the realized state in the current repetition.

A.1.3. Anderson (2001)

Both the W and the ZMK meta-datasets include the 270 decisions from the experimental condition *double payoff* of the data source.[5] In the first repetition of session 11, we corrected 5 values of the

[1] The meta-dataset is available on the website of the *American Economic Review* at *http://www.aeaweb.org/aer/data/dec2010/20080435_data.zip* (accessed May 2013).

[2] The sequence of operations which generates the ZMK meta-dataset was programmed in Mathematica and is available from the authors upon request.

[3] We downloaded the original datasets from the personal webpage of Lisa R. Anderson at *http://wmpeople.wm.edu/site/page/lrande/research* (accessed May 2013).

[4] The first author provided the original dataset.

[5] We downloaded the original dataset from the personal webpage of Lisa R. Anderson at *http://wmpeople.wm.edu/site/page/lrande/research* (accessed May 2013).

variable "his1" (which records the history in period 1) from B to A to match the values of the variable "Decision" in period 1. We also modified the last two digits of the variable "Group_id" (which is a unique identifier of the group of participants) to 11 for all decisions. Finally, we adjusted the signal quality to 2/3 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.4. Hung and Plott (2001)

The ZMK meta-dataset contains 889 decisions from the *individualistic* repetitions of the four experiments of the data source, which is one decision less than in the W meta-dataset.[6] Indeed, the experimental condition "Individ_Exp1" consists of 279 rather than 280 decisions since a signal realization is missing in the original data (period 9 of the last repetition). The ZMK meta-dataset indicates 4 different treatments with one group of participants each (as opposed to 3 different treatments and four groups in the W meta-dataset). Finally, we adjusted the signal quality to 2/3 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.5. Oberhammer and Stiehler (2003)

The ZMK meta-dataset contains only 840 of the 876 decisions contained in the W meta-dataset since we excluded the decisions from the last repetition of each session.[7] We also corrected the signal quality to 3/5 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.6. Nöth and Weber (2003)

Both the W and the ZMK meta-datasets include the 9,834 decisions of the data source.[8]

A.1.7. Kübler and Weizsäcker (2004)

The data in the ZMK meta-dataset which amount to 482 decisions match the data in the W meta-dataset except for the adjustment of the signal quality to 2/3 (the signal quality is recorded as 67/100 in the W meta-dataset).[9]

A.1.8. Drehmann, Oechssler, and Roider (2005)

Both the W and the ZMK meta-datasets contain 2,789 decisions from the experimental conditions BHW of the data source.[10] In the experimental condition "Students_55-80" (treatment 14 in the W meta-dataset), we corrected the values of the variable "NumofPlayers" from 20 to 7 for the group with 7 participants. In the experimental condition "Students_50-66" (treatment 11 in the W meta-dataset), we corrected the signal quality to 0.66 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.9. Cipriani and Guarino (2005)

Both the W and the ZMK meta-datasets contain 161 decisions from the experimental condition *fixed-price* of the data source.[11]

[6] Georg Weizsäcker kindly sent us a file with the dataset.

[7] In the dataset kindly sent to us by Georg Weizsäcker, the corresponding entries are zero and contrary to previous repetitions no decision times are registered.

[8] Markus Nöth kindly sent us the original dataset.

[9] Georg Weizsäcker kindly sent us the original dataset.

[10] The original dataset is available on the website of the *American Economic Review* at *http://www.aeaweb.org/aer/data/dec05_data_20030466.zip* (accessed May 2013).

[11] The original dataset is available on the website of the *American Economic Review* at *http://www.aeaweb.org/aer/data/dec05_data_20030357.zip* (accessed May 2013).

A.1.10. Alevy, Haigh, and List (2007)

Both the W and the ZMK meta-datasets include the 1,647 decisions of the data source.[12] We corrected two values of the variable "Session" so that the experimental condition "Students_Asymm_Loss" consists of 3 sessions with 75 decisions each (the corresponding treatment in the W meta-dataset, treatment 14, consists of 3 sessions with 76, 74 and 75 decisions, respectively) and the experimental condition "Students_Asymm_Gain" consists of 3 sessions with 75, 90 and 90 decisions, respectively (the corresponding treatment in the W meta-dataset, treatment 13, consists of 3 sessions with 76, 89 and 90 decisions, respectively). We also adjusted the signal quality to 2/3 in the symmetric conditions (the signal quality is recorded as 67/100 in the W meta-dataset), and the vector of signal qualities to $(6/7, 2/7)$ in the asymmetric conditions (the vector of signal qualities is recorded as $(85.71/100, 28.57/100)$ in the W meta-dataset).

A.1.11. Goeree, Palfrey, Rogers, and McKelvey (2007)

Both the W and the ZMK meta-datasets include the 8,760 decisions of the data source.[13] We mirrored the values of the variables "Signal", "State", "Decision", and "his$t$", $t \in \{1, \ldots, 39\}$. In the treatment with 20 periods and a signal quality equal to 5/9, the ZMK meta-dataset indicates 4 sessions with one group of participants in sessions 11, 12, and 13, and 2 groups of participants in session 14 (the W meta-dataset indicates one session with 5 groups). In the remaining three treatments, the ZMK meta-dataset indicates 3 sessions with one group of participants in each (the W meta-dataset indicates one session with 3 groups in each). Finally, we adjusted the signal quality to 5/9 in the treatments with signal quality equal to 5/9 (the signal quality is recorded as 56/100 in the W meta-dataset), and the signal quality to 6/9 in the treatments with signal quality equal to 6/9 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.12. Dominitz and Hung (2009)

The ZMK meta-dataset contains only 1,760 of the 2,270 decisions contained in the W meta-dataset since we excluded the decisions from two pilot sessions with different experimental procedures as well as the decisions from one interrupted session.[14] In the experimental condition "Replication Rounds", the ZMK meta-dataset indicates 9 sessions—3 sessions with 20 repetitions each and 6 sessions with 10 repetitions each. In the experimental condition "SLBE/ALBE Rounds", the ZMK meta-dataset indicates 6 sessions—4 sessions with 9 repetitions each and 2 sessions with 10 repetitions each. The W meta-dataset indicates one session with 12 groups of participants in treatment 11 and one session with 8 groups of participants in treatment 12. We also corrected several values of the variable "Period". Finally, we adjusted the signal quality to 2/3 (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.13. Ziegelmeyer, Koessler, Bracht, and Winter (2010)

The ZMK meta-dataset adds to the 810 decisions included in the W meta-dataset the 630 decisions of the high-informed participants. The ZMK meta-dataset therefore contains all 1,440 decisions of the data source.[15] Consequently, the values of several variables were adjusted (among others, we adjusted the values of the variable "NumofPlayers" to 16). In each of the two treatments, the ZMK meta-dataset indicates 3 sessions with one group of participants in each (the W meta-dataset indicates one session

[12] Jonathan Alevy kindly sent us the original dataset.

[13] The original dataset is available on the website of the *Review of Economic Studies* at *http://www.restud.oxfordjournals.org/content/74/3/733/suppl/DCSupplementaries* (accessed May 2013).

[14] Georg Weizsäcker kindly sent us a file with the dataset. In the W meta-dataset the 510 additional decisions are to be found in groups (of participants) 17, 18, and 19 in treatment 11 and groups 17 and 18 in treatment 12. 50 decisions belonging to group 17 of treatment 12 are wrongly indicated as group 16. The identifier of the participant indicates the correct group.

[15] The first author provided the original dataset.

with 3 groups in each treatment). We also corrected several values of the variable "Period". Finally, we adjusted the signal quality to 2/3 for the low-informed participants (the signal quality is recorded as 67/100 in the W meta-dataset).

A.1.14. Fahr and Irlenbusch (2011)

The ZMK meta-dataset contains the 1,080 decisions made by individuals in the experimental condition *private information* of the data source.[16]

A.2. Experimental Treatments in the ZMK Meta-Dataset

Most of the experimental treatments included in the ZMK meta-dataset have implemented the game of information cascades in the laboratory using a *ball-and-urn* setting.[17] There are two urns labelled A and B. Each urn contains balls with two different labels a and b. At the beginning of a repetition one of the urns is randomly selected. We denote by $p \in [1/2, 1)$ the probability that urn A is selected. Participants are randomly ordered in a sequence and each participant, without being informed of the selected urn, is invited to draw a ball (with replacement) from the unknown urn.[18] We denote by $q\,(s \mid \omega)$ the relative frequency of balls labelled s contained in the urn labelled ω where $s \in \{a, b\}$ and $\omega \in \{\mathsf{A}, \mathsf{B}\}$.[19] After observing her draw each participant is asked to predict from which urn the ball was drawn. Participants make their predictions one after another, and each participant observes the predictions made in all previous periods.[20] T denotes the number of periods in the sequence.

Below we categorize the experimental treatments included in the ZMK meta-dataset according to the structure of the *ball-and-urn* setting. We distinguish between symmetric ($p = 1/2$) and asymmetric treatments ($p \neq 1/2$), and between treatments with a unique or with multiple signal qualities.

A.2.1. Symmetric Treatments with a Unique Signal Quality

In a symmetric treatment with a unique signal quality, exactly one participant chooses an action in each period, $p = 1/2$, and the urn composition, which is identical for all participants, is given by $q\,(a \mid \mathsf{A}) = q\,(b \mid \mathsf{B}) = q \in (1/2, 1)$ and $q\,(a \mid \mathsf{B}) = q\,(b \mid \mathsf{A}) = 1 - q$. The following experimental treatments are symmetric with a unique signal quality:

- The experimental condition with *symmetric design* and without public draws in Anderson and Holt (1997) where $q = 2/3$ and $T = 6$;
- *Treatment 1* in Willinger and Ziegelmeyer (1998) where $q = 3/5$ and $T = 6$;
- The experimental condition *double payoff* in Anderson (2001) where $q = 2/3$ and $T = 6$;
- The *individualistic* repetitions of the four experiments in Hung and Plott (2001) where $q = 2/3$ and $T = 10$;
- Oberhammer and Stiehler (2003) where $q = 3/5$ and $T = 6$;

[16] René Fahr kindly sent us the original dataset.

[17] In Drehmann, Oechssler, and Roider (2005) participants have to invest into one out of two risky assets labeled A and B where only one of the assets yields a positive payoff. Each participant receives a tip from an investment banker before deciding. Participants are told that (i) absent additional information asset A yields a positive payoff in p (in %) of the cases, (ii) tips are independent, and (iii) tips are correct in q (in %) of the cases. In Cipriani and Guarino (2005) participants have to buy or sell (participants can also decide not to trade) one risky asset whose value (0 or 100) is determined by the toss of a coin. In line with the *ball-and-urn* setting each participant draws (with replacement) a chip from a bag which depending on the value of the asset contains 70 blue and 30 white chips or 30 blue and 70 white chips.

[18] In Kübler and Weizsäcker (2004) participants decide whether they want to draw a ball (for free) or not.

[19] In Nöth and Weber (2003) the composition of the urns is random. For each participant urn A (B) is equally likely to contain either three balls labelled a (b) and two balls labelled b (a) or four balls labelled a (b) and one ball labelled b (a).

[20] There are two parallel sequences in Ziegelmeyer, Koessler, Bracht, and Winter (2010). See Section A.2.4 for details.

- The experimental condition *no cost* in Kübler and Weizsäcker (2004) where $q = 2/3$ and $T = 6$;
- The experimental condition *fixed-price* in Cipriani and Guarino (2005) where $q = 7/10$ and $T = 12$;
- The experimental condition *BHW* with the a priori probability $P(\mathsf{A})$ equal to 1/2 in Drehmann, Oechssler, and Roider (2005) where $q = 0.66$ and $T = 20$;
- The experimental conditions with *symmetric design* in Alevy, Haigh, and List (2007) where $q = 2/3$ and $T \in \{5, 6\}$;
- Goeree, Palfrey, Rogers, and McKelvey (2007) where $q \in \{5/9, 2/3\}$ and $T \in \{20, 40\}$;
- Dominitz and Hung (2009) where $q = 2/3$ and $T = 10$; and
- The experimental condition with *private information* in Fahr and Irlenbusch (2011) where $q = 2/3$ and $T = 6$ (with group choices excluded).

A.2.2. Asymmetric Treatments with a Unique Signal Quality

An asymmetric treatment with a unique signal quality is identical to a symmetric treatment with a unique signal quality except that $p \neq 1/2$. The experimental conditions *BHW* with the a priori probability $P(\mathsf{A})$ strictly greater than 1/2 in Drehmann, Oechssler, and Roider (2005) are asymmetric with a unique signal quality. The considered combinations $(P(\mathsf{A}), q)$ are $(0.55, 0.60)$, $(0.51, 0.55)$, $(0.55, 0.80)$, $(0.60, 0.60)$, $(0.60, 0.51)$, and $(0.60, 0.55)$ where T varies between 5 and 20.

A.2.3. Symmetric Treatments with Multiple Signal Qualities

In a symmetric treatment with multiple signal qualities, exactly one participant chooses an action in each period and $p = 1/2$, but the composition of the urns satisfies $q\,(a \mid \mathsf{A}) \neq q\,(b \mid \mathsf{B})$ or is not the same for all participants. Different sets of urn compositions have been used in the symmetric treatments with multiple signal qualities.

In the experimental condition with *asymmetric design* of Anderson and Holt (1997), $T = 6$, and the urn composition, which is identical for all participants, is given by $q\,(a \mid \mathsf{A}) = 6/7$, $q\,(a \mid \mathsf{B}) = 5/7$, $q\,(b \mid \mathsf{A}) = 1/7$, and $q\,(b \mid \mathsf{B}) = 2/7$. The experimental conditions with *asymmetric design* in Alevy, Haigh, and List (2007) are identical except that $T \in \{5, 6\}$.

In Nöth and Weber (2003), $T = 6$ and the composition of the urns is determined randomly for each participant. With equal probability either $q\,(a \mid \mathsf{A}) = q\,(b \mid \mathsf{B}) = 3/5$ and $q\,(a \mid \mathsf{B}) = q\,(b \mid \mathsf{A}) = 2/5$ or $q\,(a \mid \mathsf{A}) = q\,(b \mid \mathsf{B}) = 4/5$ and $q\,(a \mid \mathsf{B}) = q\,(b \mid \mathsf{A}) = 1/5$.[21]

A.2.4. The Asymmetric Treatment with Multiple Signal Qualities

Only Ziegelmeyer, Koessler, Bracht, and Winter (2010) relies on an asymmetric treatment with multiple signal qualities. In this setting, $T = 9$, $p = 0.55$, and there are 16 participants divided into two sequences. Low-informed participants decide in periods 1 to 9 and draw signals from urns which satisfy $q\,(a \mid \mathsf{A}) = q\,(b \mid \mathsf{B}) = 2/3$ and $q\,(a \mid \mathsf{B}) = q\,(b \mid \mathsf{A}) = 1/3$. The predictions of these participants are publicly revealed. High-informed participants decide in periods 3 to 9 and draw from urns which satisfy $q\,(a \mid \mathsf{A}) = q\,(b \mid \mathsf{B}) = 4/5$ and $q\,(a \mid \mathsf{B}) = q\,(b \mid \mathsf{A}) = 1/5$. The predictions of the high-informed participants are not publicly revealed. Accordingly, two participants decide simultaneously in periods 3 to 9 and only the predictions of the low-informed participants are observed in subsequent periods by both

[21] The composition of the urns is determined as follows: A ball is drawn from an urn containing 10 balls labelled W and 10 balls labelled S. If the drawn ball is labelled W, urn A (B) contains three balls labelled a (b) and two balls labelled b (a). If the drawn ball is labelled S, urn A (B) contains four balls labelled a (b) and one ball labelled b (a).

types of participants.

In the ZMK meta-dataset, two experimental treatments differ if any of the values for the following variables are different: “Datasource”, “ExperimentalCondition”, or “NumofPlayers”. The ZMK meta-dataset comprises 47 different experimental treatments.

Appendix B. A General Class of Information Cascade Games

The 2-by-2-by-2 game of information cascades presented in the main text does not encompass all the experimental settings included in the ZMK meta-dataset. The information structure of the game lacks richness to generate the various pieces of information in treatments with multiple signal qualities, and in Ziegelmeyer, Koessler, Bracht, and Winter (2010) two players act simultaneously in some periods but only one of the two actions is publicly revealed.

We present here a general class of information cascade games which encompasses all settings included in the ZMK meta-dataset. As in the main text we restrict our exposition to the one-shot version of the game.

There are two payoff-relevant states of Nature (henceforth states)—state A and state B, and two possible actions—"predict state A" simply denoted by A and "predict state B" simply denoted by B.[22] Nature chooses state A with probability $p \geq 1/2$. The finite set of players is $\{1, \ldots, N\}$ with generic element n.

Nature moves first and chooses a state which remains unknown to the players. Each player is then endowed with a private signal which corresponds to the realization of a random variable, denoted by $\tilde{s}_n$, whose support is given by $\mathcal{S}$, with $\infty >\mid \mathcal{S} \mid> 1$, and whose distribution depends on the state.[23] Conditional on the state, private signals are independently distributed across players. In state A (resp. state B), player n receives signal $s_n \in \mathcal{S}$ with probability $0 < q_n(s_n \mid \mathsf{A}) < 1$ (resp. $0 < q_n(s_n \mid \mathsf{B}) < 1$) where $\sum_{\mathcal{S}} q_n(s_n \mid \mathsf{A}) = \sum_{\mathcal{S}} q_n(s_n \mid \mathsf{B}) = 1$. For each player n, the signal structure is a two-column matrix $\mathbf{Q}_n \in \mathcal{Q}$ whose rows consist of two-element vectors $(q_n(s \mid \mathsf{A}), q_n(s \mid \mathsf{B}))$, with $s \in \mathcal{S}$, and such that no two rows are identical.

Each player then makes a once-in-a-lifetime binary decision. Time is discrete, $t = 1, 2, \ldots, T$, and in each period t there are $k_t \geq 1$ players who simultaneously choose one of the two actions. The order in which players take their actions is exogenously specified with $\sum_{t=1}^{T} k_t = N$. At the beginning of each period $t \geq 2$, the action as well as the signal structure of exactly one of the players who acted in the previous period is made public. Accordingly, a player who acts in period $t \in \{1, \ldots, T\}$ observes the history $\mathbf{h}_t = ((x_1, \mathbf{Q}_1), \ldots, (x_{t-1}, \mathbf{Q}_{t-1})) \in \mathcal{H}_t = \{\{A, B\} \times \mathcal{Q}\}^{t-1}$ where $(x_\tau, \mathbf{Q}_\tau)$ is the player's action and signal structure which is public in period $\tau \in \{1, \ldots, t-1\}$, and $\mathbf{h}_1 = \emptyset$.

For all players, action A has vN-M payoffs $u(A, \mathsf{A}) = 1$ and $u(A, \mathsf{B}) = 0$, and action B has vN-M payoffs $u(B, \mathsf{A}) = 0$ and $u(B, \mathsf{B}) = 1$.

[22] Cipriani and Guarino (2005) implement a cascade game with three possible actions where the third action is an outside option whose payoff is independent of the state of Nature. All decisions where the participant or one of her predecessors chose the outside option are excluded from the meta-dataset. Therefore, theoretical predictions based on the assumption that included choices were made by players who believed the action set to be $\{A, B\}$ are identical to theoretical predictions derived from our general class of information cascade games.

[23] In the experimental condition *no cost* of Kübler and Weizsäcker (2004), participants are not automatically endowed with a private signal. The underlying cascade game includes an additional stage for players at which they are asked whether they want to costlessly obtain a signal. Not all participants asked for a signal. All observations where the participant demanded no signal are excluded from the meta-dataset. Therefore, theoretical predictions based on the avoidance of weakly dominated strategies in the additional stage are identical to theoretical predictions derived from our general class of information cascade games.

Appendix C. Decompositions of the Empirical Payoff of Actions

We here provide details for the decomposition of the empirical payoff of actions in the general class of information cascade games presented in Appendix B.

After introducing the needed notations, we first detail how to decompose the empirical payoff of actions in the simplest case where $N = T$ and the A/B symmetry is left unaddressed. Second, we present the decomposition in (A/B) symmetric experimental treatments where $N = T$. Third, we discuss the specific information cascade games underlying the experiments of Kübler and Weizsäcker (2004) and Cipriani and Guarino (2005). Finally, we detail how to decompose the empirical payoff of actions in the case where $N > T$.

Notations

A meta-dataset of information cascade experiments can be represented by a matrix with as many rows as there are participants' choices. We denote by R the total number of choices. Each row $1 \leq r \leq R$ comprises a vector of variable realizations that describe the participant's decision situation in a given period of a particular repetition of an experimental treatment. An experimental treatment is characterized by the structure of the cascade game $\left(p, N, \mathcal{S}, \{\mathbf{Q}_n\}_{n=1}^{N}, T\right)$, the number of repetitions (with randomly changing exogenous ordering between the repetitions), the experimental environment (set of instructions, payment scheme, location, etc), and the participant pool.[24] A repetition is characterized by a realized state $\omega \in \{\mathsf{A}, \mathsf{B}\}$ and a profile of signal realizations $\mathbf{s} = (s_1, s_2, \ldots, s_N) \in \mathcal{S}^N$. In each period the participant's decision situation additionally consists of the history $\mathbf{h} \in \cup_{t=1}^{T} \mathcal{H}_t$ observed by the participant and her chosen action $x \in \{A, B\}$.

Let $\mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}, x) = |\{1 \leq r \leq R \mid E_r = E, \omega_r = \omega, \mathbf{s}_r = \mathbf{s}, \mathbf{h}_r = \mathbf{h}, x_r = x\}|$ denote the number of rows in the data matrix having E as experimental treatment, ω as state, $\mathbf{s}$ as signal realizations, $\mathbf{h}$ as history, and x as chosen action.

C.1. Basic Decomposition ($N = T$, no A/B symmetry)

In period 1, W's empirical payoff of contradicting one's own signal is defined by

$$\begin{aligned} mean\_pay \mid contradict\,(E, \emptyset, s_1) \equiv & \left[\frac{\sum_{x}\sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \mathsf{A}, \mathbf{s}_{|s_1}, \emptyset, x\right)}{\sum_{\omega}\sum_{x}\sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)}\right]^{\mathbb{I}\left(\Pr(s_1|\mathsf{A})<\Pr(s_1|\mathsf{B})\right)} \\ & * \left[\frac{\sum_{x}\sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \mathsf{B}, \mathbf{s}_{|s_1}, \emptyset, x\right)}{\sum_{\omega}\sum_{x}\sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)}\right]^{\mathbb{I}\left(\Pr(s_1|\mathsf{A})>\Pr(s_1|\mathsf{B})\right)} \end{aligned}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function, $\mathbf{s}_{|s_1} \in \mathcal{S}_{|s_1}^{N}$ is a profile of signal realizations such that the signal realization of the player deciding in period 1 is s_1, $x \in \{A, B\}$, and $\omega \in \{\mathsf{A}, \mathsf{B}\}$. For any $\omega \in \{\mathsf{A}, \mathsf{B}\}$,

[24] The structure of the cascade game comprises the signal structure $\{\mathbf{Q}_n\}_{n=1}^{N}$ where each $\mathbf{Q}_n$ is a two-column matrix with as many rows as possible signal realizations and where the $\mathbf{Q}_n$ may differ across players. To facilitate the use of the ZMK meta-dataset we decided to rely on a simpler signal structure but we added a column "Treatment" which uniquely distinguishes the various experimental treatments.

$\sum_x \sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)$ equals

$$\frac{\sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)}{\sum\limits_{x} \sum\limits_{s_1 \in \mathcal{S}} \sum\limits_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)} \sum_{x} \sum_{s_1 \in \mathcal{S}} \sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right) = \widehat{\Pr}\left(s_1 \mid \omega, E, \emptyset\right) \sum_{x} \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right)$$

where $\widehat{\Pr}\left(s_1 \mid \omega, E, \emptyset\right) = \sum_x \sum_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right) / \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right)$ is the relative frequency of rows with realized signal s_1 among all rows having E as experimental treatment, ω as realized state, and $\mathbf{h}_1 = \emptyset$ as history. Moreover, $\sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right)$, equals

$$\frac{\sum\limits_{x} \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right)}{\sum\limits_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum\limits_{x} \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)} \sum_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum_{x} \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right) = \widehat{\Pr}\left(\omega \mid E, \emptyset\right) \sum_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum_{x} \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)$$

where $\widehat{\Pr}\left(\omega \mid E, \emptyset\right) = \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right) / \sum_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)$ is the relative frequency of rows with realized state ω among all rows having E as experimental treatment and $\mathbf{h}_1 = \emptyset$ as history.

Therefore, $\dfrac{\sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_1}, \emptyset, x\right)}{\sum\limits_{\omega^* \in \{\mathsf{A},\mathsf{B}\}} \sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_1}} \mathfrak{R}\left(E, \omega^*, \mathbf{s}_{|s_1}, \emptyset, x\right)}$ can be decomposed as

$$\frac{\widehat{\Pr}\left(s_1 \mid \omega, E, \emptyset\right) \widehat{\Pr}\left(\omega \mid E, \emptyset\right) \sum\limits_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum\limits_{x} \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)}{\sum\limits_{\omega^* \in \{\mathsf{A},\mathsf{B}\}} \widehat{\Pr}\left(s_1 \mid \omega^*, E, \emptyset\right) \widehat{\Pr}\left(\omega^* \mid E, \emptyset\right) \sum\limits_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum\limits_{x} \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)} = \frac{\widehat{\Pr}\left(\omega \mid E, \emptyset\right) \widehat{\Pr}\left(s_1 \mid \omega, E, \emptyset\right)}{\sum\limits_{\omega^* \in \{\mathsf{A},\mathsf{B}\}} \widehat{\Pr}\left(\omega^* \mid E, \emptyset\right) \widehat{\Pr}\left(s_1 \mid \omega^*, E, \emptyset\right)},$$

which completes the decomposition for the first period.

In period $t \geq 2$, W's empirical payoff of contradicting one's own signal is defined by

$$\begin{aligned} \mathit{mean\_pay} \mid \mathit{contradict}\left(E, \mathbf{h}_t, s_t\right) \equiv & \left[\frac{\sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \mathsf{A}, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)}{\sum\limits_{\omega} \sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)}\right]^{\mathbb{I}\left(\Pr(s_t|\mathsf{A}) < \Pr(s_t|\mathsf{B})\right)} \\ & * \left[\frac{\sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \mathsf{B}, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)}{\sum\limits_{\omega} \sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)}\right]^{\mathbb{I}\left(\Pr(s_t|\mathsf{A}) > \Pr(s_t|\mathsf{B})\right)} \end{aligned} \tag{1}$$

where $\mathbf{s}_{|s_t} \in \mathcal{S}^N_{|s_t}$ is a profile of signal realizations such that the signal realization of the player deciding in period t is s_t, $x \in \{A, B\}$, and $\omega \in \{\mathsf{A}, \mathsf{B}\}$. For any $\omega \in \{\mathsf{A}, \mathsf{B}\}$, $\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)$ equals

$$\frac{\sum\limits_{x} \sum\limits_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right)}{\sum\limits_{x} \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right)} \sum_{x} \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right) = \widehat{\Pr}\left(s_t \mid \omega, E, \mathbf{h}_t\right) \sum_{x} \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right) \tag{2}$$

where $\widehat{\Pr}\left(s_t \mid \omega, E, \mathbf{h}_t\right) = \sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right) / \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right)$ is the relative frequency of rows with realized signal s_t among all rows having E as experimental treatment, ω as realized state, and $\mathbf{h}_t$ as history. Moreover,

$$\sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right) \;=\; \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x_{t-1}\right)$$

assuming that the number of rows having E as experimental treatment and $\mathbf{h}_t$ as history equals the number of rows having E as experimental treatment, $\mathbf{h}_{t-1} \subset \mathbf{h}_t$ as history, and $x_{t-1} = \mathbf{h}_t \setminus \mathbf{h}_{t-1}$ as action.

$\sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x_{t-1}\right)$ can be decomposed as

$$\begin{aligned}
&\sum_{s_{t-1} \in \mathcal{S}} \frac{\sum\limits_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x_{t-1}\right)}{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right)} \frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right)}{\sum\limits_x \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x\right)} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x\right) \\
&= \sum_{s_{t-1} \in \mathcal{S}} \widehat{\Pr}\left(x_{t-1} \mid s_{t-1}, \mathbf{h}_{t-1}, E, \omega\right) \, \widehat{\Pr}\left(s_{t-1} \mid \omega, E, \mathbf{h}_{t-1}\right) \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x\right)
\end{aligned}$$

where $\widehat{\Pr}\left(x_{t-1} \mid s_{t-1}, \mathbf{h}_{t-1}, E, \omega\right) = \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x_{t-1}\right) / \sum_x \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right)$ is the relative frequency of rows with choice x_{t-1} among all rows having E as experimental treatment, ω as realized state, $\mathbf{h}_{t-1}$ as history, and s_{t-1} as signal realization, and $\widehat{\Pr}\left(s_{t-1} \mid \omega, E, \mathbf{h}_{t-1}\right) = \sum_x \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right) / \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x\right)$ is the estimate of $\Pr\left(s_{t-1} \mid \omega\right)$ at history $\mathbf{h}_{t-1}$. Proceeding inductively, $\sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right)$ can be decomposed as

$$\prod_{\tau < t} \sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \omega\right) \, \widehat{\Pr}\left(s_\tau \mid \omega, E, \mathbf{h}_\tau\right) \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right). \tag{3}$$

As before,

$$\sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right) = \widehat{\Pr}\left(\omega \mid E, \emptyset\right) \sum_{\omega' \in \{\mathsf{A}, \mathsf{B}\}} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right). \tag{4}$$

Finally, replacing the numerators and denominators of equation (1) with the corresponding decomposed terms in equations (2) – (4) and simplifying enables us to conclude that $mean\_pay \mid contradict(E, \mathbf{h}_t, s_t)$ equals

$$\begin{aligned}
&\left\{\left[1 + \frac{\widehat{\Pr}\left(\mathsf{B} \mid E, \emptyset\right)}{\widehat{\Pr}\left(\mathsf{A} \mid E, \emptyset\right)} \frac{\widehat{\Pr}\left(s_t \mid \mathsf{B}, E, \mathbf{h}_t\right)}{\widehat{\Pr}\left(s_t \mid \mathsf{A}, E, \mathbf{h}_t\right)} \prod_{\tau < t} \frac{\sum\limits_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \mathsf{B}, E, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{B}\right)}{\sum\limits_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \mathsf{A}, E, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{A}\right)}\right]^{-1}\right\}^{\mathbb{I}\left(\Pr(s_t \mid \mathsf{A}) < \Pr(s_t \mid \mathsf{B})\right)} \\
&* \left\{\left[1 + \frac{\widehat{\Pr}\left(\mathsf{A} \mid E, \emptyset\right)}{\widehat{\Pr}\left(\mathsf{B} \mid E, \emptyset\right)} \frac{\widehat{\Pr}\left(s_t \mid \mathsf{A}, E, \mathbf{h}_t\right)}{\widehat{\Pr}\left(s_t \mid \mathsf{B}, E, \mathbf{h}_t\right)} \prod_{\tau < t} \frac{\sum\limits_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \mathsf{A}, E, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{A}\right)}{\sum\limits_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \mathsf{B}, E, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{B}\right)}\right]^{-1}\right\}^{\mathbb{I}\left(\Pr(s_t \mid \mathsf{A}) > \Pr(s_t \mid \mathsf{B})\right)},
\end{aligned}$$

which completes the decomposition for periods $t \geq 2$.

C.2. Decomposition in Symmetric Treatments

Many of the experimental treatments included in the ZMK meta-dataset are treatments with A/B symmetry. We denote by $E^{\mathsf{A}/\mathsf{B}}$ an experimental treatment with A/B symmetry. The underlying information cascade game of such a treatment is characterized by $p = 1/2$, and, for each player $n \in N$, $\mathbf{Q}_n$ is such that for each $s \in \mathcal{S}$ there exists $\overline{s} \in \mathcal{S}$ with $q_n(\overline{s} \mid \mathsf{A}) = q_n(s \mid \mathsf{B})$ and $q_n(\overline{s} \mid \mathsf{B}) = q_n(s \mid \mathsf{A})$. Given $1 \leq t \leq T$, $s_t \in \mathcal{S}$, and $\mathbf{h}_t \in \mathcal{H}_t$, $\mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)$ denotes the number of rows in the data matrix having $E^{\mathsf{A}/\mathsf{B}}$ as experimental treatment, ω as realized state, $\mathbf{s}_{|\overline{s}_t}$ as the profile of signal realizations where the signal of the player deciding in period t is given by the (unique) signal $\overline{s}_t \in \mathcal{S}$ satisfying $q_t(\overline{s}_t \mid \mathsf{A}) = q_t(s_t \mid \mathsf{B})$ and $q_t(\overline{s}_t \mid \mathsf{B}) = q_t(s_t \mid \mathsf{A})$, $\overline{\mathbf{h}}_t = ((\overline{x}_1, \mathbf{Q}_1), \ldots, (\overline{x}_{t-1}, \mathbf{Q}_{t-1}))$ as history where $\overline{x}_\tau = A$ (B) iff $x_\tau = B$ (A) for each $\tau = 1, \ldots, t-1$, and x as chosen action. In treatments with A/B symmetry

$$
\begin{aligned}
&\textit{mean\_pay} \mid \textit{contradict}\left(E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t, s_t\right) \\
\equiv &\left[\frac{\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \mathsf{A}, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right) + \sum_x \sum_{\mathbf{s}_{|\overline{s}_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \mathsf{B}, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)}{\sum_\omega \left[\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right) + \sum_x \sum_{\mathbf{s}_{|\overline{s}_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)\right]}\right]^{\mathbb{I}\left(\Pr(s_t|\mathsf{A})<\Pr(s_t|\mathsf{B})\right)} \\
&* \left[\frac{\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \mathsf{B}, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right) + \sum_x \sum_{\mathbf{s}_{|\overline{s}_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \mathsf{A}, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)}{\sum_\omega \left[\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|s_t}, \mathbf{h}_t, x\right) + \sum_x \sum_{\mathbf{s}_{|\overline{s}_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)\right]}\right]^{\mathbb{I}\left(\Pr(s_t|\mathsf{A})>\Pr(s_t|\mathsf{B})\right)},
\end{aligned}
$$

and $\textit{mean\_pay}|\textit{contradict}\left(E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t, \overline{s}_t\right) = \textit{mean\_pay}|\textit{contradict}\left(E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t, s_t\right)$.

The same reasoning as the one used in the previous subsection implies that $\sum_x \sum_{\mathbf{s}_{|\overline{s}_t}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega, \mathbf{s}_{|\overline{s}_t}, \overline{\mathbf{h}}_t, x\right)$ equals

$$
\begin{aligned}
&\widehat{\Pr}\left(\omega \mid E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_1\right) \widehat{\Pr}\left(\overline{s}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t\right) \prod_{\tau<t} \sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_\tau\right) \widehat{\Pr}\left(\overline{x}_\tau \mid s_\tau, \overline{\mathbf{h}}_\tau, E^{\mathsf{A}/\mathsf{B}}, \omega\right) \\
&* \sum_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E^{\mathsf{A}/\mathsf{B}}, \omega', \mathbf{s}, \overline{\mathbf{h}}_1, x\right).
\end{aligned}
$$

Since $\overline{\mathbf{h}}_1 = \mathbf{h}_1 \equiv \emptyset$, $\textit{mean\_pay} \mid \textit{contradict}\left(E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t, s_t\right)$ can therefore be decomposed as

$$
\frac{\widehat{\Pr}\left(\mathsf{A} \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \widehat{\Pr}\left(s_t \mid \mathsf{A}, E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t\right) \widehat{\Pr}\left(\mathbf{h}_t \mid \mathsf{A}, E^{\mathsf{A}/\mathsf{B}}\right) + \widehat{\Pr}\left(\mathsf{B} \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \widehat{\Pr}\left(\overline{s}_t \mid \mathsf{B}, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t\right) \widehat{\Pr}\left(\overline{\mathbf{h}}_t \mid \mathsf{B}, E^{\mathsf{A}/\mathsf{B}}\right)}{\sum_\omega \widehat{\Pr}\left(\omega \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \left(\widehat{\Pr}\left(s_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t\right) \widehat{\Pr}\left(\mathbf{h}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right) + \widehat{\Pr}\left(\overline{s}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t\right) \widehat{\Pr}\left(\overline{\mathbf{h}}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right)\right)}
$$

if $\Pr(s_t \mid \mathsf{A}) < \Pr(s_t \mid \mathsf{B})$ and as

$$
\frac{\widehat{\Pr}\left(\mathsf{B} \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \widehat{\Pr}\left(s_t \mid \mathsf{B}, E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t\right) \widehat{\Pr}\left(\mathbf{h}_t \mid \mathsf{B}, E^{\mathsf{A}/\mathsf{B}}\right) + \widehat{\Pr}\left(\mathsf{A} \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \widehat{\Pr}\left(\overline{s}_t \mid \mathsf{A}, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t\right) \widehat{\Pr}\left(\overline{\mathbf{h}}_t \mid \mathsf{A}, E^{\mathsf{A}/\mathsf{B}}\right)}{\sum_\omega \widehat{\Pr}\left(\omega \mid E^{\mathsf{A}/\mathsf{B}}, \emptyset\right) \left(\widehat{\Pr}\left(s_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_t\right) \widehat{\Pr}\left(\mathbf{h}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right) + \widehat{\Pr}\left(\overline{s}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_t\right) \widehat{\Pr}\left(\overline{\mathbf{h}}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right)\right)}
$$

if $\Pr(s_t \mid \mathsf{A}) > \Pr(s_t \mid \mathsf{B})$ where

$$
\begin{aligned}
\widehat{\Pr}\left(\mathbf{h}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right) &= \prod_{\tau<t} \sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E^{\mathsf{A}/\mathsf{B}}, \omega\right), \\
\text{and } \widehat{\Pr}\left(\overline{\mathbf{h}}_t \mid \omega, E^{\mathsf{A}/\mathsf{B}}\right) &= \prod_{\tau<t} \sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \omega, E^{\mathsf{A}/\mathsf{B}}, \overline{\mathbf{h}}_\tau\right) \widehat{\Pr}\left(\overline{x}_\tau \mid s_\tau, \overline{\mathbf{h}}_\tau, E^{\mathsf{A}/\mathsf{B}}, \omega\right).
\end{aligned}
$$

C.3. Decomposition with Repetitions of Unequal Length

In the game implemented by Cipriani and Guarino (2005) players have an outside option whose payoff is independent of the state of Nature. All observations where a participant or one of her predecessors chose the outside option are excluded from the ZMK meta-dataset. Accordingly, the dataset consists of repetitions with an unequal number of periods.

In treatments where repetitions have an unequal number of periods, the empirical payoff of actions for a given period $t > 1$ relies only on repetitions for which period t exists. Indeed, this ensures that $\sum_x \sum_{\mathbf{s}} \mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}_t, x) = \sum_{\mathbf{s}} \mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x_{t-1})$ holds. Hence, in treatments where repetitions have an unequal number of periods, $mean\_pay \mid contradict(E, \mathbf{h}_t, s_t)$ equals

$$\left\{\left[1 + \frac{\widehat{\Pr}_t(\mathsf{B} \mid E, \emptyset)}{\widehat{\Pr}_t(\mathsf{A} \mid E, \emptyset)} \frac{\widehat{\Pr}_t(s_t \mid \mathsf{B}, E, \mathbf{h}_t)}{\widehat{\Pr}_t(s_t \mid \mathsf{A}, E, \mathbf{h}_t)} \prod_{\tau<t} \frac{\sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}_t(s_\tau \mid \mathsf{B}, E, \mathbf{h}_\tau)\ \widehat{\Pr}_t(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{B})}{\sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}_t(s_\tau \mid \mathsf{A}, E, \mathbf{h}_\tau)\ \widehat{\Pr}_t(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{A})}\right]^{-1}\right\}^{\mathbb{I}\left(\Pr(s_t|\mathsf{A})<\Pr(s_t|\mathsf{B})\right)}$$

$$* \left\{\left[1 + \frac{\widehat{\Pr}_t(\mathsf{A} \mid E, \emptyset)}{\widehat{\Pr}_t(\mathsf{B} \mid E, \emptyset)} \frac{\widehat{\Pr}_t(s_t \mid \mathsf{A}, E, \mathbf{h}_t)}{\widehat{\Pr}_t(s_t \mid \mathsf{B}, E, \mathbf{h}_t)} \prod_{\tau<t} \frac{\sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}_t(s_\tau \mid \mathsf{A}, E, \mathbf{h}_\tau)\ \widehat{\Pr}_t(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{A})}{\sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}_t(s_\tau \mid \mathsf{B}, E, \mathbf{h}_\tau)\ \widehat{\Pr}_t(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \mathsf{B})}\right]^{-1}\right\}^{\mathbb{I}\left(\Pr(s_t|\mathsf{A})>\Pr(s_t|\mathsf{B})\right)},$$

where $\widehat{\Pr}_t(\omega \mid E, \emptyset)$, $\widehat{\Pr}_t(s_\rho \mid \omega, E, \mathbf{h}_\rho)$, and $\widehat{\Pr}_t(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \omega)$ are the estimates of $\Pr(\omega)$ in period 1, $\Pr(s_\rho \mid \omega)$ at history $\mathbf{h}_\rho$, $\rho \leq t$, and $\Pr(x_\tau \mid s_\tau, \mathbf{h}_\tau)$ at state $\omega \in \{\mathsf{A}, \mathsf{B}\}$, respectively, *and* each estimate relies only on repetitions for which the decisions of at least the first t periods are incorporated in the dataset.[25]

C.4. Decomposition in Kübler and Weizsäcker (2004)

In Kübler and Weizsäcker (2004) participants are not automatically endowed with a private signal but asked in an additional stage whether they want to costlessly obtain a signal. Not all participants asked for a signal. All observations where the participant demanded no signal are excluded from the ZMK meta-dataset. However, the decomposition of the empirical payoff of actions relies on such observations in repetitions where a participant demands a signal after having observed the choice of a participant who demanded no signal. To compute the empirical payoff of contradicting one's own signal for all observations where participants demanded a signal, our estimation procedure first builds a temporary dataset which includes the missing observations. The added observations are dropped once empirical payoffs are computed.

Let $s =$ no denote the value of the signal variable if a player did not ask for a signal and let $\hat{\mathcal{S}} = \mathcal{S} \cup \{\text{no}\}$. Accordingly, $\sum_x \sum_{\mathbf{s}} \mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}_t, x)$ equals

$$\sum_{s_{t-1} \in \hat{\mathcal{S}}} \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x_{t-1}\right)$$

$$= \sum_{s_{t-1} \in \hat{\mathcal{S}}} \frac{\sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x_{t-1}\right)}{\sum_x \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right)} \frac{\sum_x \sum_{\mathbf{s}_{|s_{t-1}}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}}, \mathbf{h}_{t-1}, x\right)}{\sum_x \sum_{\mathbf{s}} \mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x)} \sum_x \sum_{\mathbf{s}} \mathfrak{R}(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x).$$

[25] To facilitate the computation of empirical payoffs of contradicting one's own signal for treatments with repetitions of unequal length, our estimation procedure adds a temporary variable which records the number of periods of each repetition.

By induction, $\sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right)$ can be further decomposed as

$$\prod_{\tau<t} \sum_{s_\tau \in \hat{\mathcal{S}}} \frac{\sum\limits_{\mathbf{s}_{|s_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_\tau}, \mathbf{h}_\tau, x_\tau\right)}{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_\tau}, \mathbf{h}_\tau, x\right)} \frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_\tau}, \mathbf{h}_\tau, x\right)}{\sum\limits_x \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_\tau, x\right)} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \emptyset, x\right). \tag{5}$$

Define

$$\widehat{\Pr}\left(\text{no}_\tau \mid \omega, E, \mathbf{h}_\tau\right) \equiv \frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|\text{no}_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|\text{no}_\tau}, \mathbf{h}_\tau, x\right)}{\sum\limits_x \sum\limits_{\mathbf{s}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_\tau, x\right)}, \tag{6}$$

the estimate of $\Pr\left(\text{no}_\tau \mid \omega\right)$ at history $\mathbf{h}_\tau$,

$$\widehat{\Pr}\left(x_\tau \mid \text{no}_\tau, \mathbf{h}_\tau, E, \omega\right) = \frac{\sum\limits_{\mathbf{s}_{|\text{no}_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|\text{no}_\tau}, \mathbf{h}_\tau, x_\tau\right)}{\sum\limits_x \sum\limits_{\mathbf{s}_{|\text{no}_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|\text{no}_\tau}, \mathbf{h}_\tau, x\right)} \tag{7}$$

the estimate of $\Pr\left(x_\tau \mid \text{no}_\tau, \mathbf{h}_\tau\right)$ at state ω, and

$$\widehat{\Pr}\left(s_\tau \mid \omega, E, \mathbf{h}_\tau, \text{yes}_\tau\right) = \frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_\tau}, \mathbf{h}_\tau, x\right)}{\sum\limits_x \sum\limits_{s_\tau \in \mathcal{S}} \sum\limits_{\mathbf{s}_{|s_\tau}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_\tau, x\right)} \tag{8}$$

the estimate of $\Pr\left(s_\tau \mid \omega\right)$ estimated across rows of the dataset where the experimental treatment is E, the realized state is ω, the history is $\mathbf{h}_\tau$, and the player obtained a signal. Combining equations (2), (4), and (5) – (8) implies that $\sum_x \sum_{\mathbf{s}_{|s_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right)$ equals

$$\widehat{\Pr}\left(\omega \mid E, \emptyset\right)\ \widehat{\Pr}\left(s_t \mid \omega, E, \mathbf{h}_t\right)\ \widehat{\Pr}_{\hat{\mathcal{S}}}\left(\mathbf{h}_t \mid \omega, E\right) \sum_{\omega'} \sum_x \sum_{\mathbf{s}} \mathfrak{R}\left(E, \omega', \mathbf{s}, \emptyset, x\right)$$

where $\widehat{\Pr}_{\hat{\mathcal{S}}}\left(\mathbf{h}_\tau \mid \omega, E\right)$ equals

$$\prod_{\tau<t} \left[\widehat{\Pr}\left(\text{no}_\tau \mid \omega, E, \mathbf{h}_\tau\right) \widehat{\Pr}\left(x_\tau \mid \text{no}_\tau, \mathbf{h}_\tau, E, \omega\right) \ + \ \left(1 - \widehat{\Pr}\left(\text{no}_\tau \mid \omega, E, \mathbf{h}_\tau\right)\right) \sum_{s_\tau \in \mathcal{S}} \widehat{\Pr}\left(s_\tau \mid \omega, E, \mathbf{h}_\tau, \text{yes}_\tau\right) \widehat{\Pr}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau, E, \omega\right)\right].$$

The decomposition of *mean_pay* $|$*contradict*$(E, \mathbf{h}_t, s_t)$ follows straightforwardly as in previous subsections. Note that the estimates $\widehat{\Pr}\left(\omega \mid E, \emptyset\right)$ and $\widehat{\Pr}\left(s_\tau \mid \omega, E, \mathbf{h}_\tau, \text{yes}_\tau\right)$, $s_\tau \in \mathcal{S}$, are replaced by their true counterparts in the empirical payoff of actions with *true* information parameters, but the estimates $\widehat{\Pr}\left(\text{no}_\tau \mid \omega, E, \mathbf{h}_\tau\right)$ are maintained.

C.5. Decomposition in Treatments with Multiple Choices per Period

In all experimental treatments included in the W meta-dataset exactly one player chooses an action in each period and the signal structure is identical for all players. W's counting technique is however applicable to treatments in which several players with possibly different signal structures simultaneously choose actions in each period and the action and signal structure of exactly one of these players is publicly revealed to players in subsequent periods. Ziegelmeyer, Koessler, Bracht, and Winter (2010) is such a treatment and it is included in the ZMK meta-dataset.

We denote by $\mathbf{Q} = (\mathbf{Q}_1, \ldots, \mathbf{Q}_N) \in \mathcal{Q}^N$ a profile of signal structures. Let s_t and $\mathbf{Q}_t$ denote the signal and signal structure of some player deciding in period t and denote by s_t^* and $\mathbf{Q}_t^*$ the signal and signal structure of the player whose decision and signal structure are made public in period t. In line with signal profiles, $\mathbf{Q}_{|\mathbf{Q}_t^*}$ denotes a profile of signal structures such that the signal structure of the player deciding in period t is $\mathbf{Q}_t^*$. Moreover for $\tau < \tau'$ let $\mathbf{Q}_\tau^{\tau'} = \left(\mathbf{Q}_\tau^*, \mathbf{Q}_{\tau+1}^*, \ldots, \mathbf{Q}_{\tau'}^*\right) \in \mathcal{Q}^{1+\tau'-\tau}$ denote a subprofile of observable signal structures and let $\mathbf{Q}_{|\mathbf{Q}_\tau^{\tau'},\mathbf{Q}_t}$ denote a profile of signal structures with structures $\mathbf{Q}_\tau^*, \mathbf{Q}_{\tau+1}^*, \ldots, \mathbf{Q}_{\tau'}^*, \mathbf{Q}_t$ as indicated. Extend $\mathfrak{R}$ as follows

$$\mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}, \mathbf{h}, x\right) = \left|\left\{1 \le r \le R \mid E_r = E, \omega_r = \omega, \mathbf{s}_r = s, \mathbf{Q}_r = \mathbf{Q}, \mathbf{h}_r = \mathbf{h}, a_r = x\right\}\right|.$$

Accordingly, $\mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}, \mathbf{h}, x\right)$ denotes the number of rows in the data matrix having E as experimental treatment, ω as realized state, $\mathbf{s}$ as signal realizations, $\mathbf{Q}$ as signal structure realizations, $\mathbf{h}$ as history, and x as chosen action. In period t of treatment E where history $\mathbf{h}_t$ is observed, and the realized signal and signal structure of the player about to choose are respectively s_t and $\mathbf{Q}_t$, the empirical payoff of contradicting one's own signal is given by

$$\begin{aligned} \mathit{mean\_pay}\mid\mathit{contradict}\left(E, \mathbf{h}_t, s_t, \mathbf{Q}_t\right) \equiv & \left[\frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \mathsf{A}, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)}{\sum\limits_\omega \sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)}\right]^{\mathbb{I}\left(\mathbf{Q}_t(s_t|\mathsf{A}) < \mathbf{Q}_t(s_t|\mathsf{B})\right)} \\ & * \left[\frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \mathsf{B}, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)}{\sum\limits_\omega \sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)}\right]^{\mathbb{I}\left(\mathbf{Q}_t(s_t|\mathsf{A}) > \mathbf{Q}_t(s_t|\mathsf{B})\right)}, \end{aligned}$$

Fix ω and note first that $\sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)$ equals

$$\begin{aligned} & \frac{\sum\limits_x \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)}{\sum\limits_x \sum\limits_{s_t} \sum\limits_{\mathbf{s}_{|s_t}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_t}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right)} \sum\limits_x \sum\limits_{\mathbf{s}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right) \\ = & \widehat{\Pr}\left(s_t \mid \omega, \mathbf{Q}_t, E, \mathbf{h}_t\right) \sum\limits_x \sum\limits_{\mathbf{s}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right) \end{aligned}$$

where $\widehat{\Pr}\left(s_t \mid \omega, \mathbf{Q}_t, E, \mathbf{h}_t\right)$ is the relative frequency of rows with realized signal s_t among all rows having E as experimental treatment, ω as state, $\mathbf{Q}_t$ as the realized signal structure, and $\mathbf{h}_t$ as history. Hence, $\widehat{\Pr}\left(s_t \mid \omega, \mathbf{Q}_t, E, \mathbf{h}_t\right)$ is the estimate of $\mathbf{Q}_t\left(s_t \mid \omega\right)$ at history $\mathbf{h}_t = \left(\left(a_1, \mathbf{Q}_1^*\right), \ldots, \left(x_{t-1}, \mathbf{Q}_{t-1}^*\right)\right)$. Moreover,

$$\sum\limits_x \sum\limits_{\mathbf{s}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_t}, \mathbf{h}_t, x\right) = \sum\limits_{\mathbf{s}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}, \mathbf{h}_{t-1}, x_{t-1}\right)$$

if the dataset is consistent, i.e. if the number of rows having E as experimental treatment, $\mathbf{Q}_t$ as relevant signal structure of the player deciding in period t, and $\mathbf{h}_t$ as history equals the number of rows having the same experimental treatment, $\mathbf{h}_{t-1}$ as history, x_{t-1} as action and $\mathbf{Q}_{t-1}^*$ as the signal structure of the player whose decision and signal structure are made in public in period $t-1$. Additionally,

$$\sum\limits_{\mathbf{s}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}, \mathbf{h}_{t-1}, x_{t-1}\right) = \sum\limits_{s_{t-1}^*} \sum\limits_{\mathbf{s}_{|s_{t-1}^*}} \sum\limits_{\mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}} \mathfrak{R}\left(E, \omega, \mathbf{s}_{|s_{t-1}^*}, \mathbf{Q}_{|\mathbf{Q}_{t-1}^{t-1},\mathbf{Q}_t}, \mathbf{h}_{t-1}, x_{t-1}\right)$$

which is equal to

$$\sum_{s^*_{t-1}} \frac{\sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x_{t-1}\right)}{\sum_x \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)} \frac{\sum_x \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)}{\sum_x \sum_{s^*_{t-1}} \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)}$$

$$* \sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)$$

$$= \sum_{s^*_{t-1}} \widehat{\Pr}\left(x^*_{t-1} \mid s^*_{t-1},\mathbf{Q}^*_{t-1},\mathbf{h}_{t-1},E,\omega,\mathbf{Q}_t\right)\ \widehat{\Pr}\left(s^*_{t-1} \mid \omega,\mathbf{Q}^*_{t-1},E,\mathbf{h}_{t-1},\mathbf{Q}_t\right)\ \sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)$$

where

$$\widehat{\Pr}\left(x^*_{t-1} \mid s^*_{t-1},\mathbf{Q}^*_{t-1},\mathbf{h}_{t-1},E,\omega,\mathbf{Q}_t\right) = \frac{\sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x_{t-1}\right)}{\sum_x \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)}$$

is the estimate of the probability that the player whose decision is observed in period $t-1$ chooses action x_{t-1} at information set $\left(s^*_{t-1},\mathbf{Q}^*_{t-1},\mathbf{h}_{t-1}\right)$ estimated across rows of the dataset having E as experimental treatment, ω as realized state, and $\mathbf{Q}_t$ as the signal structure of at least one player acting in period t and where

$$\widehat{\Pr}\left(s^*_{t-1} \mid \omega,\mathbf{Q}^*_{t-1},E,\mathbf{h}_{t-1},\mathbf{Q}_t\right) = \frac{\sum_x \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)}{\sum_x \sum_{s^*_{t-1}} \sum_{\mathbf{s}_{|s^*_{t-1}}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s}_{|s^*_{t-1}},\mathbf{Q}_{|\mathbf{Q}^{t-1}_{t-1},\mathbf{Q}_t},\mathbf{h}_{t-1},x\right)}$$

is the estimate of $\mathbf{Q}^*_{t-1}\left(s^*_{t-1} \mid \omega\right)$ estimated across rows of the dataset having E as experimental treatment, $\mathbf{h}_{t-1}$ as history, and $\mathbf{Q}_t$ as the signal structure of at least one player acting in period t. Proceeding inductively for the third term yields that $\sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s},\mathbf{Q}_{|\mathbf{Q}_t},\mathbf{h}_t,x\right)$ equals

$$\prod_{\tau<t} \sum_{s^*_\tau} \widehat{\Pr}\left(x^*_\tau \mid s^*_\tau,\mathbf{Q}^*_\tau,\mathbf{h}_\tau,E,\omega,\mathbf{Q}^{t-1}_{\tau+1},\mathbf{Q}_t\right)\ \widehat{\Pr}\left(s^*_\tau \mid \omega,\mathbf{Q}^*_\tau,E,\mathbf{h}_\tau,\mathbf{Q}^{t-1}_{\tau+1},\mathbf{Q}_t\right)$$

$$* \sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s},\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t},\emptyset,x\right)$$

where $\widehat{\Pr}\left(x^*_\tau \mid s^*_\tau,\mathbf{Q}^*_\tau,\mathbf{h}_\tau,E,\omega,\mathbf{Q}^{t-1}_{\tau+1},\mathbf{Q}_t\right)$ is the estimate of $\Pr\left(x_\tau \mid s^*_\tau,\mathbf{Q}^*_\tau,\mathbf{h}_\tau\right)$ and $\widehat{\Pr}\left(s^*_\tau \mid \omega,\mathbf{Q}^*_\tau,E,\mathbf{h}_\tau,\mathbf{Q}^{t-1}_{\tau+1},\mathbf{Q}_t\right)$ is the estimate of $\mathbf{Q}^*_\tau\left(s^*_\tau \mid \omega\right)$ at history $\mathbf{h}_\tau$, and both are estimated across rows where E is the experimental treatment, ω is the realized state, the signal structures of the players whose decisions are observed in periods $\tau+1,\ldots,t-1$ are given by $\mathbf{Q}^{t-1}_{\tau+1}$, and the signal structure of at least one player acting in period t is $\mathbf{Q}_t$. Finally, $\sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t}} \Re\left(E,\omega,\mathbf{s},\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t},\emptyset,x\right)$ can be decomposed as

$$\widehat{\Pr}\left(\omega \mid E,\emptyset,\mathbf{Q}^{t-1}_1,\mathbf{Q}_t\right)\ \sum_{\omega' \in \{\mathsf{A},\mathsf{B}\}} \sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t}} \Re\left(E,\omega',\mathbf{s},\mathbf{Q}_{|\mathbf{Q}^{t-1}_1,\mathbf{Q}_t},\mathbf{h}_1,x\right)$$

where

$$\widehat{\Pr}\left(\omega \mid E, \emptyset, \mathbf{Q}_1^{t-1}, \mathbf{Q}_t\right) = \frac{\displaystyle\sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}_1^{t-1}, \mathbf{Q}_t}} \Re\left(E, \omega, \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_1^{t-1}, \mathbf{Q}_t}, \mathbf{h}_1, x\right)}{\displaystyle\sum_{\omega' \in \{\mathsf{A}, \mathsf{B}\}} \sum_x \sum_{\mathbf{s}} \sum_{\mathbf{Q}_{|\mathbf{Q}_1^{t-1}, \mathbf{Q}_t}} \Re\left(E, \omega', \mathbf{s}, \mathbf{Q}_{|\mathbf{Q}_1^{t-1}, \mathbf{Q}_t}, \mathbf{h}_1, x\right)}$$

is the estimate of $\Pr(\omega)$ at the empty history, estimated across rows where E is the experimental treatment, the signal structures of the players whose decisions are observed in periods $1, \ldots, t-1$ are given by $\mathbf{Q}_1^{t-1}$, and the signal structure of at least one player acting in period t is given by $\mathbf{Q}_t$.

In conclusion, $mean\_pay|contradict\left(E, \mathbf{h}_t, s_t, \mathbf{Q}_t\right)$ can be decomposed as

$$\left[1 + \frac{\widehat{Pr}\left(\mathsf{B} \mid E, \emptyset, \mathbf{Q}_1^{t-1}, \mathbf{Q}_t\right)}{\widehat{Pr}\left(\mathsf{A} \mid E, \emptyset, \mathbf{Q}_1^{t-1}, \mathbf{Q}_t\right)} \frac{\widehat{\Pr}\left(s_t \mid \mathsf{B}, \mathbf{Q}_t, E, \mathbf{h}_t\right)}{\widehat{\Pr}\left(s_t \mid \mathsf{A}, \mathbf{Q}_t, E, \mathbf{h}_t\right)} \prod_{\tau < t} \frac{\sum_{s_\tau^* \in \mathcal{S}} \widehat{\Pr}\left(s_\tau^* \mid \mathsf{B}, \mathbf{Q}_\tau^*, E, \mathbf{h}_\tau, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right) \widehat{\Pr}\left(x_\tau^* \mid s_\tau^*, \mathbf{Q}_\tau^*, \mathbf{h}_\tau, E, \mathsf{B}, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right)}{\sum_{s_\tau^* \in \mathcal{S}} \widehat{\Pr}\left(s_\tau^* \mid \mathsf{A}, \mathbf{Q}_\tau^*, E, \mathbf{h}_\tau, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right) \widehat{\Pr}\left(x_\tau^* \mid s_\tau^*, \mathbf{Q}_\tau^*, \mathbf{h}_\tau, E, \mathsf{A}, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right)}\right]^{-1}$$

if $\mathbf{Q}_t\left(s_t \mid \mathsf{A}\right) < \mathbf{Q}_t\left(s_t \mid \mathsf{B}\right)$ and as

$$\left[1 + \frac{\widehat{Pr}\left(\mathsf{A} \mid E, \emptyset, \mathbf{Q}_1^{t-1}, \mathbf{Q}_t\right)}{\widehat{Pr}\left(\mathsf{B} \mid E, \emptyset, \mathbf{Q}_1^{t-1}, \mathbf{Q}_t\right)} \frac{\widehat{\Pr}\left(s_t \mid \mathsf{A}, \mathbf{Q}_t, E, \mathbf{h}_t\right)}{\widehat{\Pr}\left(s_t \mid \mathsf{B}, \mathbf{Q}_t, E, \mathbf{h}_t\right)} \prod_{\tau < t} \frac{\sum_{s_\tau^* \in \mathcal{S}} \widehat{\Pr}\left(s_\tau^* \mid \mathsf{A}, \mathbf{Q}_\tau^*, E, \mathbf{h}_\tau, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right) \widehat{\Pr}\left(x_\tau^* \mid s_\tau^*, \mathbf{Q}_\tau^*, \mathbf{h}_\tau, E, \mathsf{A}, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right)}{\sum_{s_\tau^* \in \mathcal{S}} \widehat{\Pr}\left(s_\tau^* \mid \mathsf{B}, \mathbf{Q}_\tau^*, E, \mathbf{h}_\tau, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right) \widehat{\Pr}\left(x_\tau^* \mid s_\tau^*, \mathbf{Q}_\tau^*, \mathbf{h}_\tau, E, \mathsf{B}, \mathbf{Q}_{\tau+1}^{t-1}, \mathbf{Q}_t\right)}\right]^{-1}$$

if $\mathbf{Q}_t\left(s_t \mid \mathsf{A}\right) > \mathbf{Q}_t\left(s_t \mid \mathsf{B}\right)$. As always, W's empirical payoff of contradicting one's own signal depends upon (i) the estimated choice probabilities, (ii) the estimated signal probabilities, and (iii) the prior's estimate in period 1. But the estimates relevant for calculating *mean_pay|contradict* in period t now also depend upon the sequence of signal structures $\left(\mathbf{Q}_1^*, \ldots, \mathbf{Q}_{t-1}^*\right)$ observed in period t and the signal structure in period t itself. The last property is irrelevant in Ziegelmeyer, Koessler, Bracht, and Winter (2010) as the signal structure is the same across repetitions.

Appendix D. Detailed Analysis of the ZMK Meta-Dataset

In this appendix we report more extensively on the statistical analyses discussed in Section 3 of the main text and we present the results of complementary analyses. Since the statistical analyses we perform are identical to those described in W, we refer to the latter for details.

D.1. Reluctance to Contradict One's Own Signal

Unless otherwise specified, we here only consider data which include cases with strictly more than ten occurrences of each decision situation ($sitcount\,(E, \mathbf{h}_t, s_t) > 10$). Table 1 reports the results of the weighted OLS regressions whose fitted lines are plotted in Figure 1 of the main text.

	Empirical payoff of contradicting one's own signal with information parameters which are	
	true	*estimated*
empirical payoff	-1.203***	-0.513***
	(0.119)	(0.125)
(empirical payoff)^2	4.471***	2.283***
	(0.363)	(0.371)
(empirical payoff)^3	-2.270***	-0.833***
	(0.270)	(0.273)
constant	0.091***	0.054***
	(0.009)	(0.009)
H_0: (0.5, 0.5)	-18.08	-25.85
Observations	16,287	16,287
R^2	0.355	0.265

Notes: Robust standard errors in parentheses, clustered at the group level.
*** (1%) significance level.

TABLE 1: FREQUENCY OF CONTRADICTING ONE'S OWN SIGNAL

As indicated by the robust t-statistics in the row labeled "$H_0 : (0.5, 0.5)$" of Table 1, we find a statistically significant vertical distance between the regression line and (0.5, 0.5) at any conventional level both for *mpc_trueinfo* and *mpc_estiminfo*. Whether the empirical payoff incorporates true or estimated information parameters, we strongly reject the null hypothesis that participants have rational expectations about the underlying payoffs of actions. Still, the vertical distance between the regression line and (0.5, 0.5) is statistically significantly lower with *mpc_trueinfo* than with *mpc_estiminfo* as the 99 percent confidence interval of the predicted value at *mpc_estiminfo*=0.5 and *mpc_trueinfo*=0.5 is (0.241, 0.288) and (0.298, 0.348), respectively. According to the R^2, the OLS regression better fits the data with *mpc_trueinfo* than with *mpc_estiminfo*.

Using the empirical payoff with *true* and *estimated* information parameters, we find that if participants always chose the empirically optimal action they would earn 72.83% and 72.28% of the high payoff on average, respectively. In decision situations where the empirical payoff with *true* and *estimated* information parameters is strictly greater than 1/2, the average participant earns 56.70% and 53.28% of the high payoff, respectively. In decision situations where the empirical payoff with *true* and *estimated* information parameters is lower than 1/2, the average participant earns 69.88% and 73.06% of the high payoff, respectively.[26]

[26]Results obtained when relying on the entire ZMK meta-dataset are as follows. Averaging across all observations where

Since both empirical payoffs of actions imperfectly measure the true payoff of actions, OLS estimates are inconsistent which might lead to invalid statistical inference. To reduce the biases resulting from sampling errors when testing the rational expectations hypothesis, we follow the split-sample instrumental variable (IV) method presented in W. The method requires the partitioning of the meta-dataset which is less straightforward when decomposed empirical payoffs of actions are used. A detailed discussion of this aspect of the IV method is postponed to Appendix E. Table 2 shows the regression results both using an OLS and an IV estimation method which includes an intercept and the empirical payoff of contradicting one's own signal. The regressor variable "empirical payoff^1" is the empirical payoff based on the first of the two subsamples, and the instrument for the IV regressions is the empirical payoff based on the second subsample.

	Empirical payoff of contradicting one's own signal with information parameters which are			
	true		*estimated*	
	OLS	IV	OLS	IV
empirical payoff^1	0.761***	1.007***	0.619***	0.944***
	(0.035)	(0.033)	(0.032)	(0.034)
constant	-0.051***	-0.137***	-0.012	-0.131***
	(0.010)	(0.010)	(0.011)	(0.011)
H_0: (0.5, 0.5)	-18.63	-15.06	-27.20	-18.32
Observations	21,775		21,775	
R^2	0.234	0.210	0.171	0.124

Notes: Robust standard errors in parentheses, clustered at the group level. *** (1%) significance level.

TABLE 2: FREQUENCY OF CONTRADICTING ONE'S OWN SIGNAL

Regardless of the estimation method, rational expectations are rejected at high levels of significance both for *mpc_trueinfo* and *mpc_estiminfo* (as indicated by the robust t-statistics in the row labeled "$H_0 : (0.5, 0.5)$"). The conclusion drawn from the test of rational expectations is therefore unaffected by the errors-in-variables problem. Still, IV coefficients always produce a steeper slope indicating that the OLS coefficients are attenuated due to sampling errors.[27] The attenuation of OLS coefficients is less pronounced and the reduction in the vertical distance between the regression line and (0.5, 0.5) is lower with *mpc_trueinfo* than with *mpc_estiminfo*. Regression results suggest that the errors-in-variable problem is less severe when using *mpc_trueinfo* rather than *mpc_estiminfo*.

Given the shape of the cloud of bubbles in Figure 1 of the main text, the linear univariate regression is likely to be a poor specification. Below we report on a series of estimations with squared and cubed regressors where the analysis is restricted to subsamples with large values of $sitcount\,(E, \mathbf{h}_t, s_t)$.

the empirical payoff is strictly greater than 1/2, we find that the relative frequency of optimal choice is 0.52 and 0.45 with *true* and *estimated* information parameters, respectively. Averaging across all observations where the empirical payoff is lower than 1/2, the optimal choice occurs with a relative frequency of 0.88 and 0.87 when using *true* and *estimated* information parameters, respectively. In decision situations where the empirical payoff with *true* and *estimated* information parameters is strictly greater than 1/2, the average participant earns 50.32% and 48.88% of the high payoff, respectively. In decision situations where the empirical payoff with *true* and *estimated* information parameters is lower than 1/2, the average participant earns 72.79% and 74.67% of the high payoff, respectively.

[27] Using the empirical payoff of contradicting one's own signal from the entire dataset, a univariate regression produces a slope coefficient of 0.826 and 0.706 for *true* and *estimated* information parameters, respectively.

Robustness Checks

Each of the next three tables shows regression results both using an OLS and an IV specification which includes an intercept plus linear, squared, and cubed terms of the empirical payoff of contradicting one's own signal with *true* and *estimated* information parameters. Table 3 (resp. 4 and 5) shows the results under the restriction that $sitcount\,(E, \mathbf{h}_t, s_t) > 10$ (resp. 30 and 100). As before, the regressor variable "empirical payoff[1]" is the empirical payoff based on the first of the two subsamples, and its instrument for the IV regressions is the empirical payoff based on the second subsample.

	Empirical payoff of contradicting one's own signal with information parameters which are			
	true		*estimated*	
	OLS	IV	OLS	IV
empirical payoff^1	-1.061***	-1.546***	-0.461***	-0.885***
	(0.121)	(0.169)	(0.127)	(0.270)
(empirical payoff^1)^2	4.195***	5.413***	2.145***	3.227***
	(0.378)	(0.509)	(0.384)	(0.790)
(empirical payoff^1)^3	-2.141***	-2.825***	-0.770***	-1.284**
	(0.280)	(0.390)	(0.286)	(0.611)
constant	0.079***	0.110***	0.056***	0.069***
	(0.009)	(0.013)	(0.009)	(0.020)
H_0: (0.5, 0.5)	-16.20	-15.69	-24.89	-19.03
Observations	16,287		16,287	
R^2	0.333	0.329	0.242	0.231

Notes: Robust standard errors in parentheses, clustered at the group level.
** (5%), *** (1%) significance level.

TABLE 3: FREQUENCY OF CONTRADICTING ONE'S OWN SIGNAL ($sitcount\,(E, \mathbf{h}_t, s_t) > 10$)

Regardless of the estimation method, whether the empirical payoff incorporates *true* or *estimated* information parameters, and the precision with which the regressor is measured, the null hypothesis that the true correspondence between the payoff of contradicting and its frequency goes through $(0.5, 0.5)$ is rejected at high levels of significance (as indicated by the robust t-statistics in the row labeled "H_0 : $(0.5, 0.5)$").[28] We confirm W's qualitative findings that the rational expectations hypothesis about the underlying payoff of actions is rejected and that the conclusion drawn from the test of rational expectations is unaffected by the errors-in-variables problem. However, we also confirm that deviations from rational expectations are statistically significantly less pronounced than suggested by W. For $sitcount\,(E, \mathbf{h}_t, s_t) > 10$ and the IV estimation method, the vertical distance between the regression line and (0.5, 0.5) is statistically significantly lower with *mpc_trueinfo* than with *mpc_estiminfo* as the 99 percent confidence interval of the predicted value at *mpc_estiminfo*=0.5 and *mpc_trueinfo*=0.5 is (0.243, 0.304) and (0.311, 0.364), respectively (confidence intervals do not overlap with the OLS estimation method either). The same conclusion cannot be drawn for more stringent minimum thresholds for $sitcount\,(E, \mathbf{h}_t, s_t)$.

The robustness checks also inform us about the severity of sampling errors in the two empirical payoffs of actions. If the regressor variable is the empirical payoff with *estimated* information parameters, a non-

[28] According to Stock and Yogo (2005) tests for weak instruments, we reject the null hypothesis of a weak instrument set at any conventional level for all six IV regressions which suggests that instruments are always appropriate. According to robust Durbin-Wu-Hausman tests, we reject the null hypothesis that regressors are exogenous at any conventional level for all six IV regressions which suggests that the IV estimation method should always be preferred to the OLS estimation method.

	Empirical payoff of contradicting one's own signal with information parameters which are			
	true		*estimated*	
	OLS	IV	OLS	IV
empirical payoff[1]	-0.990***	-0.990***	-0.006	-0.904***
	(0.153)	(0.181)	(0.169)	(0.235)
(empirical payoff[1])^2	3.782***	3.510***	0.540	3.185***
	(0.469)	(0.575)	(0.512)	(0.691)
(empirical payoff[1])^3	-1.614***	-1.153***	0.684*	-1.282**
	(0.365)	(0.467)	(0.393)	(0.540)
constant	0.078***	0.081***	0.025**	0.083***
	(0.011)	(0.013)	(0.011)	(0.018)
H_0: (0.5, 0.5)	-16.06	-15.98	-21.94	-18.68
Observations	12,194		12,194	
R^2	0.342	0.340	0.261	0.256

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), ** (5%), *** (1%) significance level.

TABLE 4: Frequency of Contradicting One's Own Signal ($sitcount\,(E, \mathbf{h}_t, s_t) > 30$)

	Empirical payoff of contradicting one's own signal with information parameters which are			
	true		*estimated*	
	OLS	IV	OLS	IV
empirical payoff[1]	-1.188***	-1.130***	-0.020	-0.475*
	(0.184)	(0.192)	(0.234)	(0.270)
(empirical payoff[1])^2	4.215***	3.945***	0.828	2.223***
	(0.574)	(0.592)	(0.689)	(0.820)
(empirical payoff[1])^3	-1.855***	-1.587***	0.527	-0.511
	(0.440)	(0.454)	(0.511)	(0.634)
constant	0.089***	0.089***	0.010	0.035*
	(0.012)	(0.013)	(0.015)	(0.018)
H_0: (0.5, 0.5)	-14.81	-15.84	-18.13	-15.42
Observations	7,433		7,433	
R^2	0.401	0.401	0.302	0.300

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), *** (1%) significance level.

TABLE 5: Frequency of Contradicting One's Own Signal ($sitcount\,(E, \mathbf{h}_t, s_t) > 100$)

negligible difference exists between the OLS and IV estimates no matter how precisely the regressor is measured. For $sitcount\,(E, \mathbf{h}_t, s_t) > 30$, the OLS coefficient estimate of each regressor statistically significantly differs at the 5 percent level from its IV coefficient estimate as their 95 percent confidence intervals do not overlap. The fact that IV standard errors are more than the double of OLS standard errors partly explains why a similar conclusion cannot be drawn for $sitcount\,(E, \mathbf{h}_t, s_t) > 10$. If the regressor variable is the empirical payoff with *true* information parameters, little difference exists between the OLS and IV estimates even for $sitcount\,(E, \mathbf{h}_t, s_t) > 10$. Though IV standard errors are at most 1.4 times larger than OLS standard errors, the 95 percent confidence interval of the OLS coefficient estimate of each regressor always overlaps with the 95 percent confidence interval level of its IV coefficient estimate whatever the minimum threshold for $sitcount\,(E, \mathbf{h}_t, s_t)$.

Larger differences between the OLS and IV estimates with *mpc_estiminfo* than with *mpc_trueinfo* do not originate from a higher performance of the IV estimation method with *estimated* than with *true* information parameters. In fact, Shea's (1997) measure of instrument relevance indicate that the finite-sample performance of the IV estimation method improves if the true payoff of actions is estimated by *mpc_trueinfo* rather than *mpc_estiminfo*. Partial R^2 values are (approximately) 2.5, 2, and 1.5 times larger with *mpc_trueinfo* than with *mpc_estiminfo* for $sitcount\,(E, \mathbf{h}_t, s_t) > 10$, 30, and 100, respectively.[29] In line with the partial R^2 values, the ratio of IV standard errors to OLS standard errors is always smaller with *mpc_trueinfo* than with *mpc_estiminfo*.

In summary, our robustness results indicate that the elimination of sampling errors in information parameters not only reduces the errors-in-variables problem but also increases the ability to make inferences from IV estimates.

D.2. Statistical Support for the Situational Determinants of Behavior

We here test rational expectations by controlling for the payoff of actions in regressions where the dependent variable is the frequency of choosing the empirically optimal action and other explanatory variables capture further details of the decision situation. The variable *late* takes value 1 if the participant decides in period 5 or later and it takes value 0 otherwise, the variable *counter_majority* takes value 1 if a strict majority of previous choices contradict the participant's own signal and it takes value 0 otherwise, and the variable *full_agreement* takes value 1 if previous choices unanimously consist of the same action and it takes value 0 otherwise. Tables 6 and 7 show the regression results for several model specifications controlling for the empirical payoff of choosing the optimal action with *true* and *estimated* information parameters, respectively.[30]

Our regression results confirm three of W's qualitative findings independently of whether the empirical payoff incorporates *true* or *estimated* information parameters. First, part of the situational effects on behavior can be explained by the incentives. The control variable always has a positive and strongly significant coefficient and controlling for the incentives largely affects the size of the coefficient of the other explanatory variables. Second, we find that in situations where participants observe a majority of previous choices which contradict their own signal they make the empirically optimal choice less often (as indicated by the significantly negative coefficient of the variable *counter_majority*). This finding confirms that participants often fail to contradict their own signal in decision situations where it is beneficial to do so. In line with our previous results we observe that the effect of *counter_majority* is always larger when the empirical payoff incorporates *estimated* rather than *true* information parameters. Third, we confirm that the coefficient of the variable *full_agreement* is marginally significant or insignificant in regressions which control for incentives and include the interaction term of *late* and *full_agreement*.

If the control variable is the empirical payoff with *true* information parameters, the IV coefficient of the variable *late* is always significantly negative which confirms W's finding that later players are less successful in interpreting the available information. Though not significantly so, the IV(6) coefficient of the variable *late* is also negative if the control variable is the empirical payoff with *estimated* information parameters. Overall, we believe the effect of the player's position in the decision sequence to be rather robust since the IV coefficient of the variable *late* is always significantly negative when relying on the W

[29] In all (first-stage of the) IV regressions, partial R^2 values of the linear, squared and cubed regressors are rather similar. If regressors incorporate *estimated* information parameters, partial R^2 values increase from 0.25 to 0.65 as $sitcount\,(E, \mathbf{h}_t, s_t)$ increases from 10 to 100. If regressors incorporate *true* information parameters, partial R^2 values increase from 0.62 to 0.97 as $sitcount\,(E, \mathbf{h}_t, s_t)$ increases from 10 to 100.

[30] To run these regressions, we had to partition the meta-dataset in three subsamples. See Appendix E for details.

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
late	0.058***	0.012	-0.044***	0.026**	-0.010	-0.054***
	(0.010)	(0.013)	(0.014)	(0.012)	(0.012)	(0.014)
counter_majority	-0.243***	-0.163***	-0.065***	-0.240***	-0.162***	-0.064***
	(0.012)	(0.016)	(0.020)	(0.012)	(0.016)	(0.020)
full_agreement	0.076***	0.034***	-0.017	0.051***	0.017	-0.025*
	(0.011)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)
late × full_agreement	—	—	—	0.055***	0.039*	0.019
				(0.017)	(0.020)	(0.027)
empirical payoff[1]	—	0.455***	1.016***	—	0.453***	1.013***
		(0.047)	(0.074)		(0.046)	(0.073)
constant	0.831***	0.508***	0.109*	0.848***	0.521***	0.116**
	(0.014)	(0.033)	(0.056)	(0.015)	(0.036)	(0.054)
Observations	16,307	16,307	16,307	16,307	16,307	16,307
R^2	0.096	0.143	0.072	0.097	0.144	0.072

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), ** (5%), *** (1%) significance level.

TABLE 6: FREQUENCY OF MAKING THE EMPIRICALLY OPTIMAL CHOICE WHERE THE EMPIRICAL PAYOFF INCORPORATES *True* INFORMATION PARAMETERS

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
late	0.095***	0.067***	0.025*	0.027	0.009	-0.018
	(0.011)	(0.012)	(0.014)	(0.019)	(0.018)	(0.017)
counter_majority	-0.287***	-0.224***	-0.130***	-0.281***	-0.220***	-0.127***
	(0.014)	(0.014)	(0.018)	(0.013)	(0.014)	(0.018)
full_agreement	0.082***	0.061***	0.031**	0.028	0.016	-0.003
	(0.015)	(0.015)	(0.016)	(0.022)	(0.020)	(0.017)
late × full_agreement	—	—	—	0.119***	0.101***	0.075***
				(0.022)	(0.021)	(0.025)
empirical payoff[1]	—	0.426***	1.070***	—	0.422***	1.068***
		(0.029)	(0.073)		(0.028)	(0.074)
constant	0.763***	0.464***	0.012	0.798***	0.497***	0.037
	(0.017)	(0.022)	(0.057)	(0.020)	(0.023)	(0.060)
Observations	16,307	16,307	16,307	16,307	16,307	16,307
R^2	0.112	0.164	0.047	0.116	0.167	0.050

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), ** (5%), *** (1%) significance level.

TABLE 7: FREQUENCY OF MAKING THE EMPIRICALLY OPTIMAL CHOICE WHERE THE EMPIRICAL PAYOFF INCORPORATES *Estimated* INFORMATION PARAMETERS

meta-dataset (see Appendix E).

However, the effect of the interaction term *late×full_agreement* unequivocally depends on whether the empirical payoff incorporates *true* or *estimated* information parameters (Appendix E shows that the same conclusion holds when we rely on the W meta-dataset). If the control variable is the empirical payoff with *true* information parameters, we do not confirm W's finding that participants are more successful in learning from others when the evidence conveyed by previous choices is strong and unambiguous. The coefficient of the interaction term $late \times full\_agreement$ is always positive but marginally significant and insignificant under OLS(5) and IV(6), respectively. If the control variable is the empirical payoff with *estimated* information parameters, the coefficient of the interaction term $late \times full\_agreement$ is always significantly positive (and highly so). We therefore conclude that the situational effect of strong and unambiguous evidence lacks robustness.

Appendix E. Statistical Analysis of the W Meta-Dataset

In this appendix we rely on the W meta-dataset to measure the success of social learning in information cascade experiments using the empirical payoff with *estimated* and *true* information parameters. Since the statistical analyses we perform are identical to those described in W, we refer to the latter for details.

E.1. Minor changes made to the W Meta-Dataset

Three minor changes were made to the W meta-dataset. These changes were necessary to permit the use of decomposed empirical payoffs of actions.

From the second to the sixth row of session 11 in Anderson (2001), the value of the variable which stores the history of period 1 ("his1") does not match the value of the variable which stores the action chosen in period 1 ("decision"). Since the decomposition crucially relies on the consistency of these two variables, we changed the period-1 chosen action.[31]

In Alevy, Haigh, and List (2007), session 15 in treatment 13 and session 18 in treatment 14 contain one row in excess (the last one) whereas session 16 in treatment 13 and session 19 in treatment 14 lack one row. Each case suggests a typographical error in the value of the variable "session" which we corrected.

E.2. Measures of the Success of Social Learning

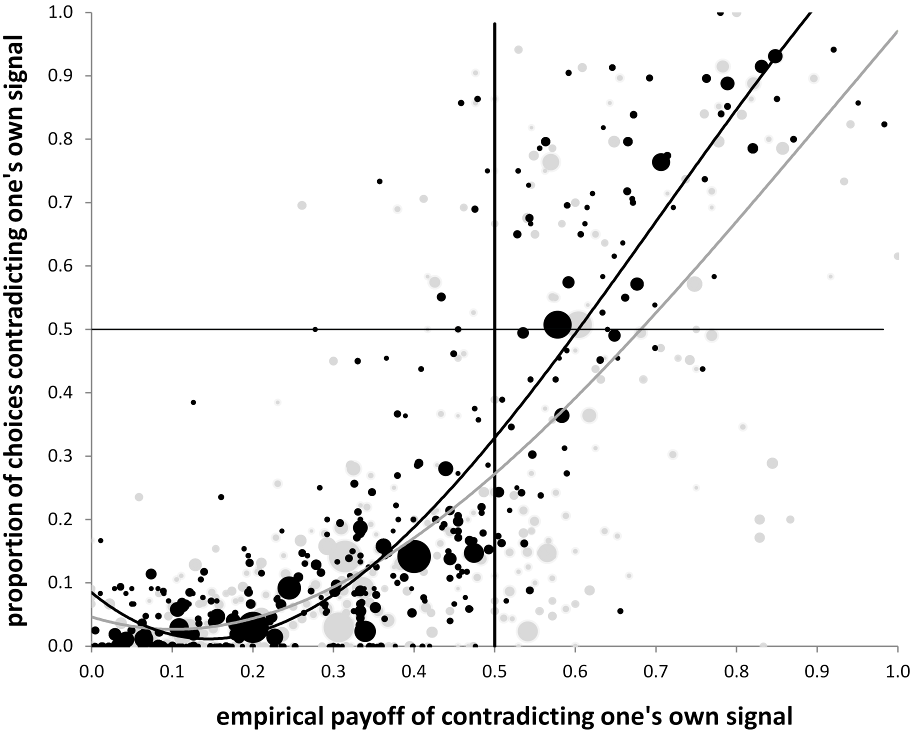
First, we report on W's statistical analyses which do not rely on the partitioning of the meta-dataset. Results obtained using the decomposed empirical payoff with *estimated* information parameters are therefore identical to W's results. Second, we report on W's statistical analyses which rely on the partitioning of the meta-dataset. Since the decomposition of the empirical payoff implies a different partitioning than the original one, results obtained using the decomposed empirical payoff with *estimated* information parameters slightly differ from those reported in W.

E.2.1. Reluctance to Contradict One's Own Signal

Unless otherwise specified, we here only consider data which include cases with strictly more than ten occurrences of each decision situation ($sitcount\,(E, \mathbf{h}_t, s_t) > 10$). Figure 1 plots the empirical payoff of contradicting one's own signal against the proportion of choices contradicting one's own signal. Black bubbles have x-values given by empirical payoffs with *true* information parameters, y-values given by associated proportions of choices contradicting one's own signal, and sizes which reflect $sitcount\,(E, \mathbf{h}_t, s_t)$. Grey bubbles have x-values given by empirical payoffs with *estimated* information parameters, y-values given by associated proportions of choices contradicting one's own signal, and sizes which reflect $sitcount\,(E, \mathbf{h}_t, s_t)$. The black and grey lines are fitted lines of weighted OLS regressions which include an intercept, and linear, squared, and cubed terms of the empirical payoff of contradicting one's own signal with *true* and *estimated* information parameters, respectively. Table 1 reports the underlying regression results.

For each empirical payoff, we find a statistically significant vertical distance between the regression line and (0.5, 0.5) at any conventional level (as indicated by the robust t-statistics in the row labeled "$H_0 : (0.5, 0.5)$" of Table 1). However, we measure a larger success of social learning when using *mpc_trueinfo* rather than *mpc_estiminfo* which confirms the findings obtained when relying on the ZMK meta-dataset. The black line reaches the level of 0.5 at an empirical payoff of contradicting one's own signal equal to 0.60 compared to 0.68 for the grey line. Averaging across all observations where the empirical payoff is strictly greater than 1/2, we find that the relative frequency of optimal choice is 0.60 and 0.44 with *true* and *estimated* information parameters, respectively. For the observations in the left-half of Figure 1, the optimal choice occurs with a relative frequency of 0.91 and 0.90 when using *mpc_trueinfo*

[31] The change implies that the action does not reflect the signal anymore. Still, we kept unchanged the value of the dummy variable which indicates whether actions reflect signals.



Note: 346 distinct values of $(E, \mathbf{h}_t, s_t)$ and 15,734 individual observations in total.

FIGURE 1: Proportion of Contradicting One's Own Signal

	Empirical payoff of contradicting one's own signal with information parameters which are	
	estimated	*true*
empirical payoff	-0.395***	-1.047***
	(0.129)	(0.130)
(empirical payoff)^2	2.067***	4.026***
	(0.383)	(0.417)
(empirical payoff)^3	-0.747**	-1.907***
	(0.286)	(0.334)
constant	0.046***	0.085***
	(0.009)	(0.009)
H_0: (0.5, 0.5)	-24.15	-16.64
Observations	15,734	15,734
R^2	0.238	0.332

Notes: Robust standard errors in parentheses, clustered at the group level.
** (5%), *** (1%) significance level.

TABLE 1: Frequency of contradicting one's own signal

and *mpc_estiminfo*, respectively (across all observations, relative frequencies of optimal choice are, respectively, 0.76 and 0.72). Using the empirical payoff of contradicting one's own signal with *true* and *estimated* information parameters, we find that if participants always chose the empirically optimal action they would earn 72.55% and 71.51% of the high payoff on average, respectively. In decision situations where *mpc_trueinfo* and *mpc_estiminfo* is strictly greater than 1/2, the average participant earns 56.24% and 52.91% of the high payoff, respectively. In decision situations where *mpc_trueinfo* and *mpc_estiminfo* is lower than 1/2, the average participant earns 69.11% and 72.20% of the high payoff, respectively.[32]

E.2.2. Analysis Based on the Partitioning of the Meta-Dataset

Preliminary Remarks on the Partitioning

To address the measurement error problem while relying on a large fraction of the data, W follows an instrumental variable approach (IV) where the instrument is obtained via the partitioning of the meta-dataset. W partitions each set of observations with identical information $(E, \mathbf{h}_t, s_t)$ in two or three subsets of (approximately) equal size.[33] Though the meta-dataset can be partitioned more or less arbitrarily when the analysis uses the original specification of the empirical payoff of actions with *estimated* information parameters, the partitioning is less straightforward when the analysis uses the decomposed empirical payoff. Indeed, observations with information $(E, \mathbf{h}_\tau, s_\tau)$ where $\tau < t$ and $\mathbf{h}_\tau \subset \mathbf{h}_t$ are required to compute the empirical payoff at information $(E, \mathbf{h}_t, s_t)$ and the set of observations must satisfy the consistency requirement

$$\sum_x \sum_{\mathbf{s}} \Re\left(E, \omega, \mathbf{s}, \mathbf{h}_t, x\right) = \sum_{\mathbf{s}} \Re\left(E, \omega, \mathbf{s}, \mathbf{h}_{t-1}, x_{t-1}\right)$$

for each E, ω, $\mathbf{s}$, and $\mathbf{h}_t$. We therefore partition the set of distinct *repetitions*[34] in two (three) subsets such that each subset contains approximately the same number of repetitions from each experimental treatment. Obviously, this way of partitioning the meta-dataset cannot ensure that the set of observations is split (almost) evenly for all information elements, and some sets of observations with a *sitcount* value of at least two (three) may not be present in both (all three) partitions.[35] Among 100 randomly generated partitionings, we chose the partitioning with the maximal number of observations whose associated information $(E, \mathbf{h}_t, s_t)$ is present in both (all three) subsets. When dividing the set of repetitions in two partitions, we end up with 20,724 observations out of the 21,670 considered by W (i.e. which satisfy $sitcount\,(E, \mathbf{h}_t, s_t) \geq 2$). When dividing the set of repetitions in three partitions, we end up with 18,679 observations out of the 20,048 considered by W (i.e. which satisfy $sitcount\,(E, \mathbf{h}_t, s_t) \geq 3$).

Reluctance to Contradict One's Own Signal (cont'd)

With the help of the two partitions of the meta-dataset, we again test the hypothesis that participants exhibit a correct perception of the payoff of actions while addressing the measurement error problem.

[32] Results obtained when relying on the entire W meta-dataset are as follows. Averaging across all observations where the empirical payoff is strictly greater than 1/2, we find that the relative frequency of optimal choice is 0.51 and 0.44 with *mpc_trueinfo* and *mpc_estiminfo*, respectively. For the observations in the left-half of Figure 1, the optimal choice occurs with a relative frequency of 0.87 and 0.86 when using *mpc_trueinfo* and *mpc_estiminfo*, respectively. In decision situations where *mpc_trueinfo* and *mpc_estiminfo* is strictly greater than 1/2, the average participant earns 49.48% and 48.26% of the high payoff, respectively. In decision situations where *mpc_trueinfo* and *mpc_estiminfo* is lower than 1/2, the average participant earns 72.23% and 73.94% of the high payoff, respectively.

[33] In experimental treatments with A/B symmetry, the set of observations also contains observations with the mirrored history and signal.

[34] In the meta-dataset, a repetition corresponds to a set of rows with the same experimental treatment, the same group of participants, and the same value for the variable *repetition*.

[35] The following minimal example illustrates the difference between the two partitionings. Consider a 3 players information cascades game which is repeated 3 times and assume that the participants' information is: $\{\emptyset, a\}$ (period 1), $\{A, a\}$ (period 2), $\{AA, a\}$ (period 3) in the first interaction; $\{\emptyset, a\}$ (period 1), $\{A, b\}$ (period 2), $\{AA, b\}$ (period 3) in the second interaction; and $\{\emptyset, b\}$ (period 1), $\{A, a\}$ (period 2), $\{AA, b\}$ (period 3) in the third interaction (for the sake of brevity we omit the variable *treatment*). Obviously, the set of observations with information $\{\emptyset, b\}$, $\{A, b\}$, or $\{AA, a\}$ cannot be partitioned since the value of *sitcount* is one. W's method partitions the set of observations with information $\{\emptyset, a\}$, $\{A, a\}$, or $\{AA, b\}$ in two equal subsets. Since we partition the set of repetitions in order to satisfy consistency, it is easy to show that none of the three possible (non-degenerate) partitions generates an even split for all the three information elements (the set of observations with information $\{\emptyset, a\}$ is not split when the first two repetitions belong to the same subset, the set $\{A, a\}$ is not split when the first and third repetitions belong to the same subset, and the set $\{AA, b\}$ is not split when the second and third repetitions belong to the same subset).

Concretely, we run a two-stage least squares IV regression in which the frequency of contradicting one's own signal is regressed on the empirical payoff of contradicting one's own signal from the first subsample and the empirical payoff of contradicting one's own signal from the second subsample serves as an instrument. For the sake of comparison, we also run an ordinary least squares regression in which the frequency of contradicting one's own signal is regressed on the empirical payoff of contradicting one's own signal from the first subsample. Table 2 shows the regression results using the empirical payoff of contradicting one's own signal with *estimated* and *true* information parameters.

	Empirical payoff of contradicting one's own signal with information parameters which are			
	estimated		*true*	
	OLS	IV	OLS	IV
empirical payoff[1]	0.570***	0.921***	0.735***	0.945***
	(0.037)	(0.038)	(0.036)	(0.030)
constant	0.009	-0.122***	-0.040***	-0.115***
	(0.013)	(0.013)	(0.011)	(0.010)
H_0: (0.5, 0.5)	-25.34	-17.97	-18.98	-17.43
Observations	20,724		20,724	
R^2	0.153	0.095	0.232	0.213

Notes: Robust standard errors in parentheses, clustered at the group level.
*** (1%) significance level.

TABLE 2: Frequency of contradicting one's own signal

Regardless of the specification and the estimate, rational expectations are rejected at high levels of significance (as indicated by the robust t-statistics in the row labeled "$H_0 : (0.5, 0.5)$"). The IV coefficients always produce a steeper slope indicating that the OLS coefficients are attenuated due to sampling errors.[36]

We again confirm the findings obtained using the ZMK meta-dataset. The attenuation of OLS coefficients is less pronounced and the true correspondence lies closer to $(0.5, 0.5)$ for the empirical payoff with *true* information parameters. The specification always fits the data better with *true* than with *estimated* information parameters (see the R^2). Robustness checks for different functional forms and subsets of the data with larger values of *sitcount* confirm these findings (results are available from the authors upon request).

Situational Determinants of Behavior

Finally, we test rational expectations by controlling for the payoff of actions in regressions where the dependent variable is the frequency of choosing the empirically optimal action and other explanatory variables capture further details of the decision situation. Regressions use the three partitions of the meta-dataset where period 1 observations are excluded. Tables 3 and 4 show the regression results for several model specifications using the empirical payoff with *estimated* and *true* information parameters, respectively.

Though the coefficients slightly differ, the regression results obtained when using the decomposed empirical payoff with *estimated* information parameters are well in line with those reported in W (Table 6 page 2354). In particular, we confirm that in situations where participants observe a majority of previous choices which contradict their own signal, they make the empirically optimal choice less often

[36]Using the empirical payoff of contradicting one's own signal from the entire dataset, a univariate regression produces a slope coefficient of 0.828 and 0.698 with *true* and *estimated* information parameters, respectively.

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
late	0.088***	0.035***	-0.049***	0.018	-0.024*	-0.090***
	(0.012)	(0.009)	(0.012)	(0.017)	(0.014)	(0.013)
counter_majority	-0.265***	-0.195***	-0.084***	-0.259***	-0.190***	-0.082***
	(0.017)	(0.016)	(0.022)	(0.016)	(0.015)	(0.022)
full_agreement	0.089***	0.057***	0.007	0.034	0.011	-0.025
	(0.018)	(0.017)	(0.016)	(0.023)	(0.022)	(0.019)
late × full_agreement	—	—	—	0.122***	0.103***	0.073***
				(0.029)	(0.024)	(0.022)
empirical payoff[1]	—	0.503***	1.294***	—	0.499***	1.282***
		(0.032)	(0.076)		(0.032)	(0.079)
constant	0.740***	0.401***	-0.131**	0.776***	0.434***	-0.102
	(0.021)	(0.024)	(0.058)	(0.024)	(0.027)	(0.063)
Observations	15,392	15,392	15,392	15,392	15,392	15,392
R^2	0.094	0.164	—	0.098	0.167	—

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), ** (5%), *** (1%) significance level.

TABLE 3: FREQUENCY OF MAKING THE EMPIRICALLY OPTIMAL CHOICE WHERE THE EMPIRICAL PAYOFF INCORPORATES *ESTIMATED* INFORMATION PARAMETERS

	OLS (1)	OLS (2)	IV (3)	OLS (4)	OLS (5)	IV (6)
late	0.028**	-0.040***	-0.076***	0.004	-0.046***	-0.074***
	(0.012)	(0.010)	(0.009)	(0.015)	(0.014)	(0.014)
counter_majority	-0.253***	-0.147***	-0.090***	-0.251***	-0.146***	-0.090***
	(0.013)	(0.015)	(0.016)	(0.013)	(0.014)	(0.015)
full_agreement	0.077***	0.021	-0.009	0.058***	0.016	-0.007
	(0.014)	(0.014)	(0.012)	(0.013)	(0.014)	(0.013)
late × full_agreement	—	—	—	0.041*	0.012	-0.004
				(0.023)	(0.018)	(0.018)
empirical payoff[1]	—	0.629***	0.966***	—	0.628***	0.966***
		(0.039)	(0.048)		(0.040)	(0.048)
constant	0.834***	0.388***	0.149***	0.846***	0.392***	0.148***
	(0.015)	(0.025)	(0.037)	(0.015)	(0.027)	(0.038)
Observations	15,392	15,392	15,392	15,392	15,392	15,392
R^2	0.095	0.182	0.157	0.096	0.182	0.157

Notes: Robust standard errors in parentheses, clustered at the group level.
* (10%), ** (5%), *** (1%) significance level.

TABLE 4: FREQUENCY OF MAKING THE EMPIRICALLY OPTIMAL CHOICE WHERE THE EMPIRICAL PAYOFF INCORPORATES *TRUE* INFORMATION PARAMETERS

(as indicated by the significantly negative coefficient of the variable *counter_majority* in all specifications). We also confirm that when controlling for the incentives later players are less successful in interpreting the available information (as indicated by the significantly negative coefficient of the variable *late* in the two IV specifications), and that participants are more successful in learning from others when the evidence conveyed by previous choices is strong and unambiguous (as indicated by the significantly positive coefficient of the variable *late* $\times$ *full_agreement* in all three specifications which include the variable).

Regression results obtained when using the empirical payoff with *true* information parameters are similar except that they do not confirm that participants are more successful in learning from others when the evidence conveyed by previous choices is strong and unambiguous (the coefficient of the variable *late* $\times$ *full_agreement* is never significantly different from zero when controlling for the incentives).

Appendix F. Sampling Errors in Empirical Payoffs of Actions

With the help of two simulation studies, we illustrate that sampling errors in information parameters contribute heavily to the overall sampling errors in W's empirical payoff of actions and that they increase the possibility of misleading inferences in testing the rational expectations hypothesis.

The first simulation study constructs 90 meta-datasets from the ZMK meta-dataset where participants' choices are replaced by simulated choices. The latter are generated according to the choice probabilities of the linear quantal response equilibrium (Rosenthal, 1989), and three values of the sensitivity to payoff differences are considered. In each simulated meta-dataset three empirical payoffs of contradicting one's own signal are calculated: the empirical payoff of contradicting one's own signal with *true* information parameters and *estimated* choice probabilities, denoted as before by *mpc_trueinfo*; the empirical payoff of contradicting one's own signal with *estimated* information parameters and *true* choice probabilities, denoted by *mpc_truechoice*; and the empirical payoff of contradicting one's own signal with *estimated* information parameters and *estimated* choice probabilities, denoted as before by *mpc_estiminfo*. Since the choice generating process is modeled, the theoretical (or true) payoff of contradicting one's own signal is known and serves as a benchmark to measure the size of sampling errors in the three empirical payoffs.

For each empirical payoff of contradicting one's own signal in each simulated meta-dataset, we regress the theoretical probability of contradicting one's own signal on an intercept plus linear term of the empirical payoff using the IV estimation method and $sitcount\,(E, \mathbf{h}_t, s_t) > 1$, 10, 30 and 100. We then test the null hypothesis that the correspondence between the true payoff of contradicting one's own signal and the probability of contradicting one's own signal goes through (0.5, 0.5) at the 1 percent level. Note that the rejection of the hypothesis amounts to a type I error (or false positive) since the rational expectations hypothesis is satisfied in the linear quantal response equilibrium—henceforth LinQRE. Moreover, the fact that the correspondence between the true payoff of contradicting one's own signal and the probability of contradicting one's own signal is linear implies that the use of LinQRE as a choice generating process ensures that linear univariate regressions have the correct functional form. The adverse effects of model misspecification on statistical inference are avoided and the IV estimation method should be able to correct for the errors-in-variables problem.[37] Our simulated meta-datasets therefore provide a best-case scenario to assess the inferential biases resulting from sampling errors in choice probabilities and information parameters. If, for a given empirical payoff of contradicting one's own signal, IV regressions often lead to the conclusion that simulated choices cannot plausibly come from better responses to rational expectations, we can be sure that sampling errors in the empirical payoff are the source of these misleading inferences.

The second simulation study also constructs 90 meta-datasets from the ZMK meta-dataset where participants' choices are replaced by simulated choices but, in addition, the realized private signals and states of Nature of all data sources are replaced with newly drawn private signals and states of Nature. As in the first study, simulated choices are generated according to LinQRE, in each simulated meta-dataset *mpc_trueinfo*, *mpc_truechoice* as well as *mpc_estiminfo* are calculated, and tests of the rational expectations hypothesis are performed. The second simulation study enables us to determine whether the results of the first study are systematic or whether they are driven by a particular set of realized signals and states.

First, we provide formal details about the quantal response equilibrium in (the general class of) information cascade games. Second, we describe the procedure to construct simulated meta-datasets and we report on the size of sampling errors in empirical payoffs of actions for the first simulation study. Third, we discuss the regression results of the first simulation study. Fourth, we report on the estimates of the

[37] For this reason, we refrained from using the (most common) logit quantal response equilibrium as a choice generating process (McKelvey and Palfrey, 1995, 1998).

information parameters in the ZMK meta-dataset. Fifth, we discuss the regression results of the second simulation study. Finally, we summarize our findings in the last part of the appendix.

F.1. Quantal Response Play in Information Cascade Games

The notion of Quantal Response Equilibrium (QRE) is based on the introduction of privately observed payoff disturbances associated with each action of each player. For player $n \in \{1, \ldots, N\}$, let

$$u_n(x, \omega) \equiv u(x, \omega) + \varepsilon_n^x,$$

where $x \in \{A, B\}$, $\omega \in \{\mathsf{A}, \mathsf{B}\}$, and the vector of disturbances $\boldsymbol{\varepsilon}_n \equiv \left(\varepsilon_n^A, \varepsilon_n^B\right)$ is drawn from a joint density f_n such that $\mathbb{E}(\boldsymbol{\varepsilon}_n) = 0$ and the marginal densities exist for each ε_n^x. Furthermore, payoff disturbances are independent across players.

Payoff disturbances translate into *quantal response functions* which describe the probabilities with which players choose each of the two available actions for a given pair of expected payoffs. Concretely, given her information set $(s_n, \mathbf{h}_t)$, Bayes-rational player n who acts in period t chooses action A if and only if[38]

$$\varepsilon_n^A + \Pr(\mathsf{A} \mid s_n, \mathbf{h}_t) \geq \varepsilon_n^B + 1 - \Pr(\mathsf{A} \mid s_n, \mathbf{h}_t),$$

and her probability to choose action A is given by

$$\sigma_n(A \mid s_n, \mathbf{h}_t) = \int_{\{\boldsymbol{\varepsilon}_n : \varepsilon_n^A - \varepsilon_n^B \geq 1 - 2\Pr(\mathsf{A} \mid s_n, \mathbf{h}_t)\}} f_n(\boldsymbol{\varepsilon}_n)\, d\boldsymbol{\varepsilon}_n = 1 - F_n\big(1 - 2\Pr(\mathsf{A} \mid s_n, \mathbf{h}_t)\big), \tag{1}$$

where $F_n\left(\varepsilon_n^A - \varepsilon_n^B\right)$ is the *realized* distribution function of the difference in player n's payoff disturbances, and $\sigma_n(B \mid s_n, \mathbf{h}_t) = 1 - \sigma_n(A \mid s_n, \mathbf{h}_t)$. Each player is independently assigned by Nature a distribution function, F_n, drawn from the commonly known set $\mathcal{F}$ and according to the commonly known distribution $\mathfrak{F}_n(F_n)$. Finally, Bayesian rationality, the game structure, and the payoffs are assumed common knowledge among the players which implies that

$$\Pr(\mathsf{A} \mid s_n, \mathbf{h}_{t+1}) = \left[1 + \frac{1 - \Pr(\mathsf{A} \mid s_n, \mathbf{h}_t)}{\Pr(\mathsf{A} \mid s_n, \mathbf{h}_t)} \frac{\sum_{s_t \in \mathcal{S}} q_t(s_t \mid \mathsf{B}) \int_{\mathcal{F}} \sigma_t(x_t \mid s_t, \mathbf{h}_t)\, d\mathfrak{F}_n(F)}{\sum_{s_t \in \mathcal{S}} q_t(s_t \mid \mathsf{A}) \int_{\mathcal{F}} \sigma_t(x_t \mid s_t, \mathbf{h}_t)\, d\mathfrak{F}_n(F)}\right]^{-1}, \tag{2}$$

where s_t is the signal realization of the player whose action $x_t \in \{A, B\}$ is public in period t, and $\Pr(\mathsf{A} \mid s_n, \mathbf{h}_1) = \Pr(\mathsf{A} \mid s_n) = (p\, q_n(s_n \mid \mathsf{A})) \,/\, (p\, q_n(s_n \mid \mathsf{A}) + (1-p)\, q_n(s_n \mid \mathsf{B}))$.

A profile of quantal response functions $(\sigma_1, \ldots, \sigma_N)$ coupled with a system of conditional probabilities which satisfy Eq. (1) and (2) is a Heterogeneous QRE.[39] In equilibrium, expectations about choice probabilities are consistent with the actual choice frequencies of the other players i.e. players have *rational expectations* (thanks to the heterogeneity of quantal response functions being structurally common knowledge).[40]

[38] More precisely, Bayes-rational player n forms a belief $b(s_n, \mathbf{h}_t) = \left[1 + \frac{1-p}{p} \frac{q_n(s_n \mid \mathsf{B})}{q_n(s_n \mid \mathsf{A})} \frac{\Pr(\mathbf{h}_t \mid \mathsf{B})}{\Pr(\mathbf{h}_t \mid \mathsf{A})}\right]^{-1}$ which maps information sets into probability estimates that the realized state of Nature is A. She then maximizes her expected payoff $E[u(x, \tilde{\omega}) \mid s_n, \mathbf{h}_t]$ where $E[u(A, \tilde{\omega}) \mid s_n, \mathbf{h}_t] = b(s_n, \mathbf{h}_t) + \varepsilon_n^A$ and $E[u(B, \tilde{\omega}) \mid s_n, \mathbf{h}_t] = 1 - b(s_n, \mathbf{h}_t) + \varepsilon_n^B$ ($\tilde{\omega}$ is a random variable with support $\{\mathsf{A}, \mathsf{B}\}$ and $\Pr(\tilde{\omega} = \mathsf{A}) = p$). To save on notation, we dispense with beliefs.

[39] The equilibrium can be derived by iterative reasoning, under the numerous assumptions we made, obviating the usual fixed-point argument.

[40] Rogers, Palfrey, and Camerer (2009) introduce *subjective expectations* about the structural heterogeneity of quantal response functions to define the concept of Subjective Heterogeneous QRE. This solution concept provides an intuitive link between QRE models and models with levels of strategic sophistication.

Linear QRE Choices and the Payoff of Contradicting One's Own Signal

We now derive the expected payoff of contradicting one's own signal, $\pi|contradict$, assuming for simplicity that choices are generated according to a (homogeneous) linear QRE. As expected, we obtain that $\pi|contradict$ is a function of p, the signal structures, and the equilibrium choice probabilities.

LinQRE is a parametric class of QRE parameterized by $\lambda \in [0, 1/2]$, the sensitivity to payoff differences, and with a *linear* quantal response function defined by

$$\sigma^{\lambda}(A \mid s, \mathbf{h}) \equiv \frac{1}{2} + \lambda\left(2\Pr\left(\mathsf{A} \mid s, \mathbf{h}\right) - 1\right),$$

with $s \in \mathcal{S}$ and $\mathbf{h} \in \cup_{t=1}^{T} \mathcal{H}_t$.

Given $(s_n, \mathbf{h}_t)$, player n's expected payoff of contradicting her signal in period t is defined by

$$\pi \mid contradict\,(s_n, \mathbf{h}_t) \equiv \Pr\left(\mathsf{A} \mid s_n, \mathbf{h}_t\right)^{\mathbb{I}\left(\Pr(s_n|\mathsf{A})<\Pr(s_n|\mathsf{B})\right)}\left(1 - \Pr\left(\mathsf{A} \mid s_n, \mathbf{h}_t\right)\right)^{\mathbb{I}\left(\Pr(s_n|\mathsf{A})>\Pr(s_n|\mathsf{B})\right)},$$

where $\mathbb{I}$ denotes the indicator function, and if choices are generated according to LinQRE we obtain that

$$\Pr\left(\mathsf{A} \mid s_n, \mathbf{h}_t\right) = \left[1 + \frac{(1-p)\, q_n\left(s_n \mid \mathsf{B}\right)}{p\, q_n\left(s_n \mid \mathsf{A}\right)} \prod_{\tau<t} \frac{\sum_{s_\tau \in \mathcal{S}} q_\tau\left(s_\tau \mid \mathsf{B}\right)\ \sigma^{\lambda}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau\right)}{\sum_{s_\tau \in \mathcal{S}} q_\tau\left(s_\tau \mid \mathsf{A}\right)\ \sigma^{\lambda}\left(x_\tau \mid s_\tau, \mathbf{h}_\tau\right)}\right]^{-1} \tag{3}$$

for $t \geq 2$ where s_τ is the signal realization of the player whose action $x_\tau \in \{A, B\}$ is public in period τ, and $\Pr(\mathsf{A} \mid s_n, \mathbf{h}_1) = \Pr(\mathsf{A} \mid s_n) = \left(p\, q_n\left(s_n \mid \mathsf{A}\right)\right) / \left(p\, q_n\left(s_n \mid \mathsf{A}\right) + (1-p)\, q_n\left(s_n \mid \mathsf{B}\right)\right)$.

Player n's probability to contradict her signal at information set $(s_n, \mathbf{h}_t)$ is given by $y\left(\pi \mid contradict\right) = \frac{1}{2} + \lambda\left(2\,\pi \mid contradict - 1\right)$. Obviously, the probability to contradict one's own signal is a linear function of $\pi|contradict$ such that $y(1/2) = 1/2$ for all $1/2 \geq \lambda \geq 0$.

Linear QRE Choices in Kübler and Weizsäcker (2004)

In the cascade game underlying the experimental condition *no cost* in Kübler and Weizsäcker (2004) players decide in two stages. In the first stage, player n who acts in period t at history $\mathbf{h}_t$ decides whether to receive a signal for free or not. If player n receives a signal then her information set becomes $(s_n, \mathbf{h}_t)$, otherwise it remains $(\mathbf{h}_t)$. In the second stage, player n chooses either action A or B.

In LinQRE of this game players employ the linear quantal response function when choosing actions in the second stage. Action A is chosen with probability $\sigma^{\lambda}(A \mid s, \mathbf{h})$ in case a signal has been received in the first stage and with probability

$$\sigma^{\lambda}(A \mid \mathbf{h}) \equiv \frac{1}{2} + \lambda\left(2\Pr\left(\mathsf{A} \mid \mathbf{h}\right) - 1\right)$$

in case no signal has been received in the first stage. The expected payoffs associated with receiving a signal or not are respectively

$$V\left(\text{signal} \mid \mathbf{h}\right) = \Pr\left(\mathsf{A} \mid \mathbf{h}\right) \sum_{s \in \mathcal{S}} q_n\left(s \mid \mathsf{A}\right) \sigma^{\lambda}(A \mid s, \mathbf{h}) \; + \; \Pr\left(\mathsf{B} \mid \mathbf{h}\right) \sum_{s \in \mathcal{S}} q_n\left(s \mid \mathsf{B}\right) \left[1 - \sigma^{\lambda}(A \mid s, \mathbf{h})\right], \text{and}$$

$$V\left(\text{no signal} \mid \mathbf{h}\right) = \Pr\left(\mathsf{A} \mid \mathbf{h}\right)\ \sigma^{\lambda}(A \mid \mathbf{h}) \; + \; \Pr\left(\mathsf{B} \mid \mathbf{h}\right)\ \left[1 - \sigma^{\lambda}(A \mid \mathbf{h})\right].$$

Therefore, the probability to ask for a signal in the first stage is given by

$$\Pr\left(\text{signal} \mid \mathbf{h}\right) = \frac{1}{2} + \lambda\left(V\left(\text{signal} \mid \mathbf{h}\right) - V\left(\text{no signal} \mid \mathbf{h}\right)\right).$$

Assuming that Bayesian rationality, $\lambda \in [0, 1/2]$, the game structure, and the payoffs are common knowledge implies that

$$\Pr(\mathsf{A} \mid \mathbf{h}_t) = \left[1 + \frac{(1-p)}{p} \prod_{\tau<t} \frac{\Pr(\text{no signal} \mid \mathbf{h}_\tau)\ \sigma^\lambda(x_\tau \mid \mathbf{h}_\tau)\ +\ \Pr(\text{signal} \mid \mathbf{h}_\tau) \sum_{s_\tau \in \mathcal{S}} q_\tau(s_\tau \mid \mathsf{B})\ \sigma^\lambda(x_\tau \mid s_\tau, \mathbf{h}_\tau)}{\Pr(\text{no signal} \mid \mathbf{h}_\tau)\ \sigma^\lambda(x_\tau \mid \mathbf{h}_\tau)\ +\ \Pr(\text{signal} \mid \mathbf{h}_\tau) \sum_{s_\tau \in \mathcal{S}} q_\tau(s_\tau \mid \mathsf{A})\ \sigma^\lambda(x_\tau \mid s_\tau, \mathbf{h}_\tau)}\right]^{-1}$$

and

$$\Pr(\mathsf{A} \mid s_n, \mathbf{h}_t) = \left[1 + \frac{q_n(s_n \mid \mathsf{B})}{q_n(s_n \mid \mathsf{A})} \frac{\Pr(\mathsf{B} \mid \mathbf{h}_t)}{\Pr(\mathsf{A} \mid \mathbf{h}_t)}\right]^{-1}.$$

Since decisions where the participant did not ask for a signal are excluded from the meta-dataset, the expected payoff of contradicting one's own signal and the probability to contradict one's own signal are defined as before.

Linear QRE Choices in Cipriani and Guarino (2005)

Cipriani and Guarino (2005) implement a cascade game with three possible actions where the third action is an outside option O whose payoff is such that $0 < u(O, \mathsf{A}) = u(O, \mathsf{B}) \equiv u(O) < 1$. In LinQRE of this game with extended action set, player n's probability to contradict one's own signal is strictly smaller than 1/2 if the payoff to contradict one's own signal equals 1/2 (i.e. $y(1/2) < 1/2$). To avoid such a discrepancy, we assume that the action set of the cascade game underlying the experimental condition *fixed-price* in Cipriani and Guarino (2005) is given by $\{A, B\}$.

F.2. Simulated Meta-Datasets and Size of Sampling Errors with the Realized Signals and States of the Data Sources

We first provide some details about the construction of simulated meta-datasets and then we report on the size of sampling errors for each of the three empirical payoffs of actions.

F.2.1. Construction of a Simulated Meta-Dataset

Assume $1/2 \geq \lambda \geq 0$. First, a preliminary meta-dataset is created by deleting all choice data and associated variables from the ZMK meta-dataset.[41] Second, for each experimental treatment, choice data are simulated and the true as well as the three empirical payoffs of contradicting one's own signal are calculated for each row of the meta-dataset. Concretely, in a given experimental treatment, the preliminary meta-dataset is completed period-by-period as follows:

- In rows where the decision period is 1: a) The true payoff of contradicting one's own signal is calculated, and the true probability of contradicting one's own signal is determined using the quantal response function and λ; b) Choices are determined randomly and independently across repetitions, groups, and sessions;[42] c) Estimated information parameters and estimated choice probabilities are calculated; and d) Empirical payoffs of contradicting one's own signal are calculated using the estimated information parameters for *mpc_estiminfo* and *mpc_truechoice*.

[41] We describe only the main operations required to construct a simulated meta-dataset. Additional minor operations are necessary to cope with the specificities of some data sources, in particular Kübler and Weizsäcker (2004) and Cipriani and Guarino (2005). The sequence of operations which generates a simulated meta-dataset was programmed in Mathematica and is available from the authors upon request.

[42] For each row, a number is drawn from a uniform distribution on $[0, 1]$. If the signal indicates state A, the choice is A (B) if the realized number is larger (smaller) than the probability of contradicting one's own signal. If the signal indicates state B, the choice is B (A) if the realized number is larger (smaller) than the probability of contradicting one's own signal.

- In rows where the decision period is $t > 1$: a) Based on simulated choices for periods $\tau < t$, histories are created; b) The true payoff of contradicting one's own signal is calculated, and the true probability of contradicting one's own signal is determined using the quantal response function and λ; c) Choices are determined randomly and independently across repetitions, groups, and sessions; d) Estimated information parameters and estimated choice probabilities are calculated; e) Empirical payoffs of contradicting one's own signal are calculated using the estimated choice probabilities for periods $\tau < t$ in the case of *mpc_estiminfo* and *mpc_trueinfo* and the estimated information parameters for periods $\tau \leq t$ in the case of *mpc_estiminfo* and *mpc_truechoice*.

Three values of the sensitivity to payoff differences are considered: $\lambda = 0.125$, 0.25, and 0.5. For each λ, 30 simulated meta-datasets are generated.

F.2.2. Size of Sampling Errors in Empirical Payoffs of Actions

Since the choice generating process is modeled, we can precisely measure the size of sampling errors in each of the three empirical payoffs of contradicting one's own signal. For a given simulated meta-dataset and a given empirical payoff of contradicting one's own signal, the size of sampling errors is measured by the standard deviation of the difference between the true and the empirical payoff of contradicting one's own signal. Table 5 reports for each λ the distribution of the standard deviation of the difference between the true payoff of contradicting one's own signal and each of the three empirical payoffs of contradicting one's own signal. The size of sampling errors in each of the three empirical payoffs of contradicting one's own signal decreases as the sensitivity to payoff differences increases. This is to be expected as a higher λ implies more extreme QRE choice probabilities which in turn leads to less variation in generated histories and better estimates of choice probabilities and information parameters.[43] Another unsurprising observation is that *mpc_estiminfo* has the largest sampling errors of the three empirical payoffs of contradicting one's own signal. More importantly, the size of sampling errors in *mpc_trueinfo* is statistically significantly lower than the size of sampling errors in *mpc_truechoice* (for any λ, the largest sampling errors in *mpc_trueinfo* are smaller than the smallest sampling errors in *mpc_truechoice*). On the other hand, sampling errors in *mpc_truechoice* are of similar size as sampling errors in *mpc_estiminfo*. We therefore conclude that sampling errors in information parameters contribute heavily to the overall sampling errors in W's empirical payoff of actions if choices are generated according to LinQRE.

F.3. Statistical Analysis of the Simulated Meta-Datasets with the Realized Signals and States of the Data Sources

For each of the 90 simulated meta-datasets and each of the three empirical payoffs of contradicting one's own signal, we regress the theoretical probability of contradicting one's own signal on an intercept plus linear term of the empirical payoff using the IV estimation method and $sitcount\,(E, \mathbf{h}_t, s_t) > 1$, 10, 30 and 100. We then test whether the vertical distance between the regression line and (0.5, 0.5) is statistically significantly different from zero at the 1 percent level.[44] Table 6 reports for each λ and each empirical payoff of contradicting one's own signal the number of occurrences where the distance is non-significantly different from zero and the number of occurrences where the distance is significantly different from zero. If the distance is found to be statistically significantly different from zero, the rational expectations hypothesis is incorrectly rejected meaning that a false positive occurs. False positives which result from the predicted value at x-value=0.5 being statistically significantly lower than 0.5 are denoted by "Down

[43] Estimates of the signal qualities are computed at the history level which implies that they are more precisely measured the less variation in generated histories. The fact that estimates of the signal qualities are computed at the history level also explains why the distribution of *mpc_truechoice* changes across simulation runs despite the fact that true choice probabilities as well as realized signals and states do not change.

[44] Unlike in the statistical analysis of the W and ZMK meta-datasets which relies on robust standard errors clustered at the group level, we here rely on conventional standard errors.

		mpc_trueinfo	*mpc_truechoice*	*mpc_estiminfo*
$\lambda = \frac{1}{8}$	Min	0.286	0.302	0.304
	1^{st} quartile	0.289	0.303	0.306
	Median	0.289	0.304	0.306
	3^{rd} quartile	0.290	0.305	0.307
	Max	0.292	0.306	0.309
$\lambda = \frac{1}{4}$	Min	0.281	0.297	0.299
	1^{st} quartile	0.286	0.301	0.303
	Median	0.287	0.302	0.304
	3^{rd} quartile	0.288	0.303	0.305
	Max	0.291	0.305	0.307
$\lambda = \frac{1}{2}$	Min	0.274	0.290	0.291
	1^{st} quartile	0.276	0.293	0.295
	Median	0.277	0.295	0.296
	3^{rd} quartile	0.279	0.296	0.297
	Max	0.285	0.301	0.304

TABLE 5: Size of Sampling Errors in
Empirical Payoffs of Contradicting One's Own Signal

Reject" whereas false positives which result from the predicted value at x-value=0.5 being statistically significantly higher than 0.5 are denoted by "Up Reject". If the null hypothesis that the predicted value at x-value=0.5 equals 0.5 cannot be rejected, a "No Reject" occurs. The median of the predicted value at x-value=0.5 is shown in columns "$\hat{y}(0.5)$" with the median of the standard error in parentheses.[45]

If the regressor variable is *mpc_trueinfo*, the median of the predicted value at x-value=0.5 either equals 0.5 or is extremely close to 0.5 in all instances (with the mild exceptions of $sitcount\,(E, \mathbf{h}_t, s_t) > 1$ when $\lambda = 1/4$ or $1/2$). Though only a minority of the test results are negative, there is often a quite even number of "Down Reject" and "Up Reject" (rejections of the rational expectations hypothesis are largely driven by the small *conventional* standard errors of the coefficient estimates). In accordance with the choice generating process, regression results indicate that choices can be considered as better responses to rational expectations.

Quite different results are observed if the regressor variable is *mpc_truechoice*. The median of the predicted value at x-value=0.5 is always below 0.5 and the difference is rather large for $\lambda = 1/4$ and $1/2$. The rational expectations hypothesis is almost always rejected since the predicted value at x-value=0.5 is usually found to be statistically significantly lower than 0.5 (far larger standard errors of the coefficient estimates would still lead to rejections of the rational expectations hypothesis). These results indicate that the use of *mpc_truechoice* as an estimate of the true payoff of contradicting one's own signal leads to systematic misleading inferences. Given our sample size, the IV estimation method is unable to fully correct for inference problems due to sampling errors in information parameters.

Results for *mpc_estiminfo* are similar to those observed for *mpc_truechoice* which is in line with the fact that sampling errors in information parameters contribute heavily to the overall sampling errors in W's empirical payoff of actions.

The results of the statistical analysis of the simulated meta-datasets suggest that, though the empirical

[45]Since the choice generating process is modeled, an alternative test of the rational expectations hypothesis consists in testing whether the coefficient estimates statistically significantly differ from the true coefficients. This alternative formulation of the test leads to the same qualitative conclusions.

	sitcount $(E, \mathbf{h}_t, s_t)$	***mpc_trueinfo*** Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)	***mpc_truechoice*** Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)	***mpc_estiminfo*** Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)
$\lambda = \frac{1}{8}$	> 1	17	9	4	0.496 (0.001)	30	0	0	0.480 (0.001)	28	2	0	0.480 (0.001)
	> 10	11	7	12	0.500 (0.000)	30	0	0	0.477 (0.000)	30	0	0	0.478 (0.000)
	> 30	10	6	14	0.500 (0.000)	30	0	0	0.481 (0.000)	30	0	0	0.481 (0.000)
	> 100	14	2	14	0.500 (0.000)	30	0	0	0.482 (0.001)	29	1	0	0.482 (0.001)
$\lambda = \frac{1}{4}$	> 1	18	6	6	0.491 (0.002)	28	2	0	0.464 (0.002)	27	3	0	0.465 (0.002)
	> 10	15	5	10	0.499 (0.001)	30	0	0	0.460 (0.001)	30	0	0	0.459 (0.001)
	> 30	16	5	9	0.499 (0.000)	30	0	0	0.467 (0.001)	30	0	0	0.465 (0.001)
	> 100	15	4	11	0.500 (0.000)	30	0	0	0.470 (0.001)	30	0	0	0.470 (0.001)
$\lambda = \frac{1}{2}$	> 1	23	5	2	0.482 (0.002)	30	0	0	0.445 (0.002)	30	0	0	0.447 (0.003)
	> 10	23	3	4	0.495 (0.001)	30	0	0	0.439 (0.001)	30	0	0	0.437 (0.001)
	> 30	16	4	10	0.497 (0.000)	30	0	0	0.448 (0.001)	30	0	0	0.445 (0.001)
	> 100	17	0	13	0.498 (0.000)	30	0	0	0.460 (0.002)	30	0	0	0.456 (0.002)

Notes: Columns "Down Reject" report rejections of the rational expectations hypothesis for the cases where the predicted value at x-value=0.5 is statistically significantly lower than 0.5 at the 1 percent level. Columns "No Reject" report nonrejections of the rational expectations hypothesis as the predicted value at x-value=0.5 is not statistically significantly different from 0.5 at the 1 percent level. Columns "Up Reject" report rejections of the rational expectations hypothesis for the cases where the predicted value at x-value=0.5 is statistically significantly higher than 0.5 at the 1 percent level. Columns "$\hat{y}(0.5)$" report the median of the predicted value at x-value=0.5 with the median of the standard error in parentheses.

TABLE 6: Nonrejections and Rejections of the Rational Expectations Hypothesis

payoff of contradicting one's own signal with *true* information parameters accurately estimates the true payoff of contradicting one's own signal, empirical payoffs of contradicting one's own signal with *estimated* information parameters often overestimate the true payoff of contradicting one's own signal. Supporting evidence for this conjecture is provided by the distributions of average differences between the true payoff of contradicting one's own signal—henceforth *mpc_true*—and each of the three empirical payoffs of contradicting one's own signal for $\lambda \in \{0.125, 0.25, 0.5\}$ and *sitcount* $(E, \mathbf{h}_t, s_t) > 0$, 10, 30 and 100. We report on the differences between *mpc_true* and each of the three empirical payoffs of contradicting one's own signal by distinguishing period 1 from periods 2-6 and the latest periods.

Whatever the value of the sensitivity to payoff differences and the lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$, the distribution of the average differences between *mpc_true* and *mpc_truechoice* is hardly distinguishable from the distribution of the average differences between *mpc_true* and *mpc_estiminfo*. We therefore do not report on the average differences between *mpc_true* and *mpc_truechoice*. Moreover, the range of average differences is always narrow with a size of less than 0.01 except for the empirical payoffs with *estimated* information parameters in periods 2-6 where $\lambda = 0.5$ and *sitcount* $(E, \mathbf{h}_t, s_t) > 100$ (0.017 and 0.016 for *mpc_truechoice* and *mpc_estiminfo*, respectively).

In period 1, *mpc_estiminfo* accurately estimates the true payoff of contradicting one's own signal for any λ and lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$. The largest absolute value of the difference between *mpc_true* and *mpc_estiminfo* equals 0.006. By definition, *mpc_trueinfo* = *mpc_true* in period 1.

In periods 2-6, *mpc_estiminfo* systematically overestimates *mpc_true* for any λ and lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$. In each simulated meta-dataset the average difference between *mpc_true* and *mpc_estiminfo* is negative and the median of these average differences is about -0.05. Given a lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$ the distribution of average differences shifts to the left as λ decreases, and given λ the distribution of average differences tends to shift to the left as the lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$ increases with similar differences for *sitcount* $(E, \mathbf{h}_t, s_t) > 10$ and *sitcount* $(E, \mathbf{h}_t, s_t) > 30$. On the contrary, for any λ and lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$, *mpc_trueinfo* accurately estimates *mpc_true* with the largest absolute value of the difference being equal to 0.006.

In periods $t > 6$, each of the three empirical payoffs of contradicting one's own signal slightly overestimates *mpc_true* for any λ and with *sitcount* $(E, \mathbf{h}_t, s_t) > 0$ (too few observations are available for larger lower bounds). In each of the nine cases, the median of the average differences either equals or is very close to -0.007.

To summarize, the use of *mpc_estiminfo* as a regressor variable leads to systematic misleading inferences in testing the rational expectations hypothesis most likely because *mpc_estiminfo* systematically overestimates *mpc_true* in some of the periods. As a consequence, the empirical correspondence between *mpc_estiminfo* and the theoretical probability to contradict one's own signal is a translation to the right of the true correspondence between *mpc_true* and the theoretical probability to contradict one's own signal. Since *mpc_trueinfo* quite accurately estimates *mpc_true*, regression results correctly indicate that choices are better responses to rational expectations when the empirical payoff incorporates the *true* information parameters.

We now examine the empirical information parameters in the ZMK meta-dataset as an attempt to determine the causes of the overestimation effect.

F.4. Empirical Priors and Signal Qualities in the ZMK Meta-Dataset

Similar qualitative differences between the regression results with *mpc_estiminfo* and *mpc_trueinfo* are observed in the ZMK and in the simulated meta-datasets. Assuming that sampling errors in information parameters have identical adverse effects in the ZMK and in the simulated meta-datasets, the extent to which *mpc_trueinfo* differs from *mpc_estiminfo* is an indicator of the overestimation effect. Table 7 shows the difference between *mpc_trueinfo* and *mpc_estiminfo* in the ZMK meta-dataset. For a given period and a given lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$, a cell in the table reports the quartiles of the distribution of this difference as well as the number of rows in the meta-dataset on which the difference is calculated (periods $t > 6$ are summarized into one row of the table).

With the exception of period 1, *mpc_estiminfo* is larger than *mpc_trueinfo* in the majority of the rows. In periods $t > 6$ there are very few observations with identical information $(E, \mathbf{h}, s)$ and there is often no variance in the realized state across these observations. The latter implies that *mpc_trueinfo* $=$ *mpc_estiminfo* $\in \{0, 1\}$ which is why the difference between *mpc_trueinfo* and *mpc_estiminfo* is zero in most of these rows. The empirically optimal action changes from contradicting one's own signal when relying on *mpc_estiminfo* to following one's own signal when relying on *mpc_trueinfo* in 8 to 10% of the rows, but it changes in the opposite direction in only about 2% of the rows.

To elucidate the underlying reasons for the overestimation effect, we examine the empirical information parameters in the ZMK meta-dataset. First, we discuss the difference between the empirical priors $\widehat{\Pr}(\mathsf{A} \mid E, \emptyset)$ and the true priors p in the ZMK meta-dataset. The quartiles of the distribution of this difference are shown in Table 8 for various thresholds of the underlying number of observations $\sum_\omega \sum_x \sum_\mathbf{s} \mathfrak{R}(E, \omega, \mathbf{s}, \emptyset, x)$. Though the median lies slightly below zero for each threshold, the distribution centers around zero and its spread shrinks as the number of observations increases. We conclude that prior probabilities are reasonably well estimated.

Period	Sitcount > 0		Sitcount > 10		Sitcount > 30		Sitcount > 100	
	Rows	Quartiles	Rows	Quartiles	Rows	Quartiles	Rows	Quartiles
		-0.106		-0.106		-0.106		-0.106
t = 1	3,429	0.021	3,321	0.021	2,933	0.029	2,195	0.033
		0.086		0.086		0.086		0.086
		-0.091		-0.091		-0.091		-0.091
t = 2	3,427	-0.026	3,145	-0.026	2,454	-0.026	1,760	-0.026
		0.010		-0.003		-0.012		-0.026
		-0.084		-0.084		-0.066		-0.091
t = 3	3,514	-0.005	2,831	-0.005	2,118	-0.005	1,639	-0.005
		0.083		0.081		0.114		0.115
		-0.11		-0.11		-0.121		-0.057
t = 4	3,511	-0.032	2,485	-0.034	1,821	-0.034	956	-0.032
		0.052		0.039		0.001		0.001
		-0.108		-0.113		-0.119		-0.119
t = 5	3,502	0	2,140	-0.038	1,595	-0.060	513	-0.060
		0.048		0.048		0.048		0.048
		-0.133		-0.144		-0.144		-0.071
t = 6	3,333	-0.015	1,922	-0.071	1,118	-0.071	370	-0.028
		0		0		-0.027		0
		0		-0.130		-0.130		-
t > 6	10,370	0	443	-0.071	155	-0.106	0	-
		0		0.056		-0.098		-

TABLE 7: Difference between *mpc_trueinfo* and *mpc_estiminfo* in the *ZMK* Meta-Dataset

	1^{st} quartile	Median	3^{rd} quartile
Number of Observations > 0	-0.100	-0.033	0.083
Number of Observations > 10	-0.078	-0.033	0.006
Number of Observations > 30	-0.063	-0.018	0
Number of Observations > 100	-0.017	-0.002	0

Notes: There are 47, 37, 21, and 5 empirical priors when the number of observations is strictly greater than 0, 10, 30, and 100, respectively.

TABLE 8: Difference between Empirical and True Priors in the *ZMK* Meta-Dataset

Second, we discuss the difference between the empirical signal qualities and the true signal qualities in the *ZMK* meta-dataset.[46] For a given period and a given lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$, a cell of Table 9 reports the quartiles of the distribution of this difference as well as the number of rows in the meta-dataset on which the difference is calculated (periods $t > 6$ are summarized into one row of the table).

Empirical signal qualities tend to underestimate true signal qualities especially in later periods and for large values of *sitcount* $(E, \mathbf{h}_t, s_t)$. Assuming that the true signal quality is less than $2/3$ (which applies in more than 75 percent of the observations), about one-quarter of the empirical signal qualities are either uninformative or indicate the wrong state for most periods and lower bounds on *sitcount* $(E, \mathbf{h}_t, s_t)$ (as indicated by the first quartile of the distribution). In period $t = 6$, the same holds for about half of the empirical signal qualities (as indicated by the median of the distribution). We would like to emphasize that empirical signal qualities are biased regardless of the data source. For each data source, the empirical signal quality differs from the true one by at least one decimal point in more than 1/3 of the rows on which the difference is calculated (more than 1/2 of the rows for 11 out of 14 data sources). We conclude

[46]For a given row in the meta-dataset the true signal quality is given by $\max_s q_n (s \mid \omega)$ where ω is the realized state of Nature in the given row.

Period	Sitcount > 0		Sitcount > 10		Sitcount > 30		Sitcount > 100	
	Rows	Quartiles	Rows	Quartiles	Rows	Quartiles	Rows	Quartiles
		-0.056		-0.056		-0.056		-0.067
t = 1	3,429	0.026	3,321	0.028	2,933	0.021	2,195	0.046
		0.089		0.089		0.089		0.089
		-0.172		-0.172		-0.172		-0.201
t = 2	3,427	-0.033	3,145	-0.033	2,454	-0.062	1,760	-0.146
		0.087		0.087		0.087		-0.013
		-0.135		-0.135		-0.135		-0.135
t = 3	3,514	-0.019	2,831	-0.029	2,118	-0.042	1,639	-0.061
		0.101		0.083		0.083		0.062
		-0.197		-0.197		-0.197		-0.229
t = 4	3,511	-0.031	2,485	-0.042	1,821	-0.072	956	-0.072
		0.106		0.069		0.045		0.045
		-0.19		-0.171		-0.200		-0.215
t = 5	3,502	-0.021	2,140	-0.031	1,595	-0.044	513	-0.071
		0.120		0.083		0.083		-0.044
		-0.3		-0.305		-0.313		-0.305
t = 6	3,333	-0.133	1,922	-0.182	1,118	-0.235	370	-0.239
		0.143		0		-0.064		-0.235
		-0.556		-0.190		-0.067		-
t > 6	10,370	0.333	443	-0.020	155	-0.022	0	-
		0.400		0.200		0.230		-

TABLE 9: Difference between Empirical and True Signal Qualities in the *ZMK* Meta-Dataset

that, especially in later periods, signal qualities are imprecisely estimated and that the difference between the empirical and the true signal quality is usually negative.

While for period 1 it is straightforward to show that *mpc_estiminfo* is larger than *mpc_trueinfo* if signal qualities are underestimated,[47] the relationship is less clear in later periods as *mpc_estiminfo* $(E, \mathbf{h}_t, s_n)$ depends on estimated signal probabilities at histories $\mathbf{h}_\tau \subseteq \mathbf{h}_t$ for each $\tau \leq t$. Additional analyses suggest that the empirical signal probabilities at history $\mathbf{h}_t$ are most influential. First, we created modified versions of the empirical payoffs of contradicting one's own signal, *mpc_trueinfo*$^\clubsuit$ and *mpc_estiminfo*$^\clubsuit$, where the factor for the signal in the current period is deleted.[48] Comparing the difference between *mpc_trueinfo*$^\clubsuit$ and *mpc_estiminfo*$^\clubsuit$ to the difference between *mpc_trueinfo* and *mpc_estiminfo* enables us to separate out the influence of the empirical signal qualities at history $\mathbf{h}_t$ on *mpc_estiminfo* $(E, \mathbf{h}_t, s_n)$. We find that the median difference between *mpc_trueinfo*$^\clubsuit$ and *mpc_estiminfo*$^\clubsuit$ is *positive* for most periods $t > 1$ and most levels of *sitcount* $(E, \mathbf{h}_t, s_t)$ which indicates a strong influence of the empirical signal qualities at history $\mathbf{h}_t$. Second, we created a blend of the two empirical payoffs of actions, *mpc_partestiminfo*,

[47]Disregarding symmetry and other special cases, $\Pr(s_n \mid \mathsf{A}) < \Pr(s_n \mid \mathsf{B})$, $\Pr(s_n \mid A) < \widehat{\Pr}(s_n \mid \mathsf{A}, E, \emptyset)$, $\widehat{\Pr}(s_n \mid \mathsf{B}, E, \emptyset) < \Pr(s_n \mid B)$, and $\widehat{\Pr}(\mathsf{A} \mid E, \emptyset) \approx p$ jointly imply that *mpc_estiminfo* $(E, \emptyset, s_n) = \left[1 + \frac{\widehat{\Pr}(\mathsf{B}|E,\emptyset)}{\widehat{\Pr}(\mathsf{A}|E,\emptyset)} \frac{\widehat{\Pr}(s_n|\mathsf{B},E,\emptyset)}{\widehat{\Pr}(s_n|\mathsf{A},E,\emptyset)}\right]^{-1} > \left[1 + \frac{1-p}{p} \frac{q_n(s_n|\mathsf{B})}{q_n(s_n|\mathsf{A})}\right]^{-1} =$ *mpc_trueinfo* $(E, \emptyset, s_n)$. A similar argument applies when $\Pr(s_n \mid \mathsf{A}) > \Pr(s_n \mid \mathsf{B})$.

[48]Disregarding symmetry and other special cases, *mpc_estiminfo*$^\clubsuit$ $(E, \mathbf{h}_t, s_n) = \left[1 + \frac{(1-p)}{p} \prod_{\tau<t} \frac{\sum_{s_\tau} \widehat{\Pr}(s_\tau|\mathsf{B},E,\mathbf{h}_\tau)\, \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{B})}{\sum_{s_\tau} \widehat{\Pr}(s_\tau|\mathsf{A},E,\mathbf{h}_\tau)\, \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{A})}\right]^{-1}$ and *mpc_trueinfo*$^\clubsuit$ $(E, \mathbf{h}_t, s_n) = \left[1 + \frac{(1-p)}{p} \prod_{\tau<t} \frac{\sum_{s_\tau} \Pr(s_\tau|\mathsf{B})\, \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{B})}{\sum_{s_\tau} \Pr(s_\tau|\mathsf{A})\, \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{A})}\right]^{-1}$ if $\Pr(s_n \mid \mathsf{A}) < \Pr(s_n \mid \mathsf{B})$, and similarly if $\Pr(s_n \mid \mathsf{A}) > \Pr(s_n \mid \mathsf{B})$ with A and B interchanged.

by replacing only the empirical signal qualities at history $\mathbf{h}_t$ by the true signal qualities in *mpc_estiminfo*.[49] Results of statistical analyses identical to those in section 3, but based on *mpc_partestiminfo* are comparable to the results based on *mpc_trueinfo* (details are available from the authors upon request).

In conclusion, the fact that *mpc_estiminfo* is larger than *mpc_trueinfo* seems to originate from the fact that, especially in later periods, empirical signal qualities tend to underestimate true signal qualities in the ZMK meta-dataset. To determine the extent to which the results of the first simulation study are driven by the particular set of realized signals and states of the ZMK meta-dataset, we conduct a second simulation study with newly drawn signals and states.

F.5. Simulated Meta-Datasets with Newly Drawn Signals and States

For a given $\lambda \in [0, 1/2]$, a simulated meta-dataset is constructed the same way as before except that the realized private signals and states of Nature of all data sources are replaced with newly drawn private signals and states of Nature in the preliminary meta-dataset. In each repetition of a given experimental treatment, states of Nature and private signals are generated according to the prior and signal qualities of the treatment. First, we discuss the differences between empirical signal qualities in the ZMK and in the simulated meta-datasets. Second, we report on the size of sampling errors in the three empirical payoffs of contradicting one's own signal. Finally, we discuss the results of the tests of the rational expectations hypothesis.

Empirical Signal Qualities

Distributions of the difference between empirical and true signal qualities in the simulated meta-datasets reveal that, for most periods and lower bounds on *sitcount* $(E, \mathbf{h}_t, s_t)$, empirical signal qualities in the ZMK meta-dataset do *not* abnormally underestimate true signal qualities. Indeed, for most periods and lower bounds on *sitcount* $(E, \mathbf{h}_t, s_t)$, there exists a simulated meta-dataset whose median of the distribution of the difference between empirical and true signal qualities is lower than the corresponding median in the ZMK meta-dataset.[50] In fact, for any quartile of the distribution in the ZMK meta-dataset there exists a simulated meta-dataset with a smaller value of the quartile and a simulated meta-dataset with a larger value of the quartile. Still, the distribution in the ZMK meta-dataset is usually shifted to the left compared to most distributions in the simulated meta-datasets, and, in a few instances, the distribution in the ZMK meta-dataset is shifted to the left compared to *all* distributions in the simulated meta-datasets (this is for example the case in period $t = 6$ whatever the lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$).

Size of Sampling Errors in Empirical Payoffs of Actions

Table 10 reports for each λ the distribution of the standard deviation of the difference between the true payoff of contradicting one's own signal and each of the three empirical payoffs of contradicting one's own signal. As expected, the size of sampling errors in *mpc_trueinfo* is hardly affected by the fact that simulated meta-datasets include newly drawn signals and states. On the other hand, the size of sampling errors in *mpc_truechoice* and *mpc_estiminfo* has been slightly reduced. Part of the larger sampling errors

[49] Accordingly, *mpc_partestiminfo* $(E, \mathbf{h}_t, s_n) = \left[1 + \frac{(1-p)}{p} \frac{\Pr(s_n|\mathsf{B})}{\Pr(s_n|\mathsf{A})} \prod_{\tau<t} \frac{\sum_{s_\tau} \widehat{\Pr}(s_\tau|\mathsf{B},E,\mathbf{h}_\tau)\ \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{B})}{\sum_{s_\tau} \widehat{\Pr}(s_\tau|\mathsf{A},E,\mathbf{h}_\tau)\ \widehat{\Pr}(x_\tau|s_\tau,\mathbf{h}_\tau,E,\mathsf{A})}\right]^{-1}$ if $\Pr(s_n \mid \mathsf{A}) < \Pr(s_n \mid \mathsf{B})$, and similarly if $\Pr(s_n \mid \mathsf{A}) > \Pr(s_n \mid \mathsf{B})$ with A and B interchanged.

[50] Needless to say, the median of the medians of the distributions of the difference between empirical and true signal qualities is (almost) equal to zero in the very large majority of periods and lower bounds on *sitcount* $(E, \mathbf{h}_t, s_t)$. Most noticeable exceptions are periods $t > 6$ with *sitcount* $(E, \mathbf{h}_t, s_t) > 0$ and 30 where the median equals 0.111 and 0.023, respectively.

in empirical payoffs with *estimated* information parameters observed in the first simulation study seems to be induced by the particular set of realized signals and states of the data sources. However, the size of sampling errors in *mpc_trueinfo* remains statistically significantly smaller than the size of sampling errors in *mpc_truechoice* and *mpc_estiminfo*, and sampling errors in information parameters still contribute heavily to the overall sampling errors in W's empirical payoff of actions.

		mpc_trueinfo	*mpc_truechoice*	*mpc_estiminfo*
$\lambda = \frac{1}{8}$	Min	0.283	0.293	0.295
	1^{st} quartile	0.287	0.296	0.298
	Median	0.288	0.297	0.299
	3^{rd} quartile	0.289	0.298	0.300
	Max	0.291	0.301	0.304
$\lambda = \frac{1}{4}$	Min	0.281	0.291	0.293
	1^{st} quartile	0.284	0.294	0.296
	Median	0.285	0.295	0.297
	3^{rd} quartile	0.286	0.296	0.298
	Max	0.290	0.300	0.302
$\lambda = \frac{1}{2}$	Min	0.272	0.283	0.285
	1^{st} quartile	0.274	0.285	0.287
	Median	0.276	0.287	0.288
	3^{rd} quartile	0.278	0.289	0.291
	Max	0.281	0.292	0.294

TABLE 10: Size of Sampling Errors in Empirical Payoffs of Contradicting One's Own Signal with Newly Drawn Signals and States

Statistical Analysis

As in the first simulation study, for each of the 90 simulated meta-datasets with newly drawn signals and states and each of the three empirical payoffs of contradicting one's own signal, we regress the theoretical probability of contradicting one's own signal on an intercept plus linear term of the empirical payoff using the IV estimation method and $sitcount\,(E, \mathbf{h}_t, s_t) > 1$, 10, 30 and 100. We then test whether the vertical distance between the regression line and (0.5, 0.5) is statistically significantly different from zero at the 1 percent level. Table 11 reports for each λ, each empirical payoff of contradicting one's own signal and each lower bound on $sitcount\,(E, \mathbf{h}_t, s_t)$ the number of occurrences where the vertical distance between the regression line and (0.5, 0.5) is non-significantly different from zero and the number of occurrences where the distance is significantly different from zero at the 1 percent level, and the median of the predicted value at x-value=0.5 with the median of the standard error in parentheses.

For each of the three empirical payoffs of contradicting one's own signal, the median of the predicted value at x-value=0.5 either equals 0.5 or is extremely close to 0.5 in all instances. Though only a minority of the test results are negative (rejections of the rational expectations hypothesis are largely driven by the small standard errors of the coefficient estimates), there is (almost) always a quite even number of "Down Reject" and "Up Reject" (with the exception of $sitcount\,(E, \mathbf{h}_t, s_t) > 1$ when $\lambda = 1/8$). We conclude that, in simulated meta-datasets with newly drawn signals and states, systematic misleading inferences are avoided whatever the empirical payoff of contradicting one's own signal.

This being said, the fact that sampling errors are significantly larger in *mpc_estiminfo* than in *mpc_trueinfo* implies that the discrepancy between the regression line and (0.5, 0.5) is (almost) always larger when the regressor is *mpc_estiminfo* than when it is *mpc_trueinfo*. Indeed, for any λ and any

		mpc_trueinfo				*mpc_truechoice*				*mpc_estiminfo*			
	sitcount $(E, \mathbf{h}_t, s_t)$	Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)	Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)	Down Reject	No Reject	Up Reject	$\hat{y}(0.5)$ (SE)
$\lambda = \frac{1}{8}$	> 1	19	9	2	0.496 (0.001)	17	6	7	0.496 (0.001)	15	11	4	0.496 (0.001)
	> 10	13	8	9	0.500 (0.000)	8	9	13	0.500 (0.000)	12	8	10	0.500 (0.001)
	> 30	14	3	13	0.500 (0.000)	10	6	14	0.501 (0.000)	13	2	15	0.501 (0.000)
	> 100	14	4	12	0.500 (0.000)	9	6	15	0.501 (0.000)	12	2	16	0.501 (0.000)
$\lambda = \frac{1}{4}$	> 1	14	5	11	0.501 (0.002)	10	12	8	0.502 (0.003)	10	9	11	0.503 (0.003)
	> 10	9	6	15	0.501 (0.001)	13	5	12	0.500 (0.001)	10	6	14	0.501 (0.001)
	> 30	9	3	18	0.502 (0.000)	13	5	12	0.499 (0.001)	10	9	11	0.500 (0.001)
	> 100	8	5	17	0.501 (0.000)	13	3	14	0.500 (0.000)	14	4	12	0.499 (0.001)
$\lambda = \frac{1}{2}$	> 1	18	8	4	0.491 (0.002)	9	12	9	0.502 (0.003)	10	11	9	0.504 (0.004)
	> 10	14	5	11	0.499 (0.001)	12	6	12	0.501 (0.001)	11	5	14	0.503 (0.002)
	> 30	16	2	12	0.497 (0.000)	13	6	11	0.499 (0.001)	12	6	12	0.500 (0.001)
	> 100	16	1	13	0.497 (0.000)	15	5	10	0.498 (0.001)	15	5	10	0.496 (0.001)

Notes: Columns "Down Reject" report rejections of the rational expectations hypothesis for the cases where the predicted value at x-value=0.5 is statistically significantly lower than 0.5 at the 1 percent level. Columns "No Reject" report nonrejections of the rational expectations hypothesis as the predicted value at x-value=0.5 is not statistically significantly different from 0.5 at the 1 percent level. Columns "Up Reject" report rejections of the rational expectations hypothesis for the cases where the predicted value at x-value=0.5 is statistically significantly higher than 0.5 at the 1 percent level. Columns "$\hat{y}(0.5)$" report the median of the predicted value at x-value=0.5 with the median of the standard error in parentheses.

TABLE 11: Nonrejections and Rejections of the Rational Expectations Hypothesis with Newly Drawn Signals and States

lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$ except *sitcount* $(E, \mathbf{h}_t, s_t) > 1$ and $\lambda \in \{1/8, 1/2\}$, the range of predicted values at x-value=0.5 for *mpc_estiminfo* includes the range of predicted values at x-value=0.5 for *mpc_trueinfo*, and the vertical distance between the regression line and (0.5, 0.5) for *mpc_estiminfo* is from 5/4 to 5/2 times the vertical distance between the regression line and (0.5, 0.5) for *mpc_trueinfo*. Clearly, deviations of simulated choices from better responses to rational expectations are larger when the regressor is the empirical payoff of contradicting one's own signal with *estimated* information parameters than when the regressor is the empirical payoff of contradicting one's own signal with *true* information parameters. Moreover, the predicted values at x-value=0.5 induced by the realized signals and states of the data sources, though they are low, do not abnormally underestimate 0.5. For any λ and *sitcount* $(E, \mathbf{h}_t, s_t) > 1$, the range of predicted values at x-value=0.5 induced by the realized signals and states of the data sources overlaps with the range of predicted values at x-value=0.5 induced by the newly drawn signals and states.

The regression results of the two simulation studies suggest that *mpc_estiminfo* more accurately estimates *mpc_true* in simulated meta-datasets with newly drawn signals and states than in simulated meta-datasets with the realized signals and states of the data sources. In fact, newly drawn signals and states have two major impacts on the distributions of the average difference between *mpc_true* and *mpc_estiminfo*. First, for any λ and lower bound on *sitcount* $(E, \mathbf{h}_t, s_t)$, the median of the distribution of the average difference between *mpc_true* and *mpc_estiminfo* is close to zero in period 1 and in late periods but also in periods

2-6. The systematic overestimation effect in periods 2-6 is therefore absent and, indeed, *mpc_estiminfo* is often an accurate estimate of *mpc_true*. Second, the range of average differences between *mpc_true* and *mpc_estiminfo* is 2 to 6 times wider than the range of average differences between *mpc_true* and *mpc_trueinfo* (as expected, newly drawn signals and states hardly affect the distributions of the average difference between *mpc_true* and *mpc_trueinfo*). For example, in periods 2-6, the smallest and largest average difference between *mpc_true* and *mpc_estiminfo* (respectively *mpc_trueinfo*) equals -0.019 and 0.017 (respectively -0.002 and 0.004) for $\lambda = 0.125$ and $sitcount\,(E, \mathbf{h}_t, s_t) > 100$. In certain simulated meta-datasets with newly drawn signals and states, *mpc_estiminfo* remains a much worse estimate of *mpc_true* than *mpc_trueinfo*, but the reverse never holds.

F.6. Conclusion

Our two simulation studies illustrate that sampling errors in information parameters contribute heavily to the overall sampling errors in *mpc_estiminfo* which implies that if empirical information parameters substantially mis-estimate true information parameters then the use of *mpc_estiminfo* as a control variable leads to systematic misleading inferences in testing the rational expectations hypothesis. The possible adverse effects of sampling errors in information parameters are avoided in regression analyses which control for the incentives by including *mpc_trueinfo*.

In simulated meta-datasets with the realized signals and states of the data sources, empirical signal qualities tend to underestimate true signal qualities and, as a consequence, *mpc_estiminfo* systematically overestimates the true payoff of contradicting one's own signal in some periods. In tests of the rational expectations hypothesis, the use of *mpc_estiminfo* as an estimate of the true payoff of contradicting one's own signal therefore leads to systematic biased conclusions. On the other hand, regression results correctly indicate that choices are better responses to rational expectations when the empirical payoff of contradicting one's own signal incorporates the *true* information parameters.

In simulated meta-datasets with newly drawn signals and states, *mpc_estiminfo* is often an accurate estimate of the true payoff of contradicting one's own signal and, as a consequence, systematic misleading inferences are avoided in tests of the rational expectations hypothesis whatever the regressor variable. Still, in some of the simulated meta-datasets with newly drawn signals and states, *mpc_estiminfo* remains a much worse estimate of the true payoff of contradicting one's own signal than *mpc_trueinfo* and regression results indicate that deviations of simulated choices from better responses to rational expectations are larger with *mpc_estiminfo* than with *mpc_trueinfo*.

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