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Anthony Ziegelmeyer
Christoph March
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Friedrich Schiller University Jena
Carl-Zeiss-Str. 3
D-07743 Jena
www.uni-jena.de

Max Planck Institute of Economics
Kahlaische Str. 10
D-07745 Jena
www.econ.mpg.de

"Do We Follow Others when We Should? A Simple Test of Rational Expectations": Comment*

Anthony Ziegelmeyer[†], Christoph March[‡] and Sebastian Krügel[§]

Abstract

Weizsäcker (2010) estimates the payoff of actions to test rational expectations and to measure the success of social learning in information cascade experiments. He concludes that participants perform poorly when learning from others and that rational expectations are violated. We show that his estimated payoffs rely on estimates of the publicly known prior and signal qualities which may lead the formulated test of rational expectations to generate false positives. We rely on the true values of the prior and signal qualities to estimate the payoff of actions. We confirm that the rational expectations hypothesis is rejected, but we measure a much larger success of social learning.

Keywords: Information Cascades; Laboratory Experiments; Quantal Response Equilibrium

JEL Classification: C92; D82

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†Corresponding author: Max Planck Institute of Economics, Kahlaische Strasse 10, 07745 Jena, Germany. Email: ziegelmeyer@econ.mpg.de.

‡Paris School of Economics, 48 Boulevard Jourdan, 75014 Paris, France. Email: march@pse.ens.fr

§Max Planck Institute of Economics, IMPRS "Uncertainty", Kahlaische Strasse 10, 07745 Jena, Germany. Email: kruegel@econ.mpg.de.

1 Introduction

Weizsäcker (2010)—henceforth W—presents an appealing reduced-form approach to measure the success of social learning in information cascade experiments. The payoff of actions is estimated and the resulting estimate is controlled for in regression analyses to assess the extent to which participants respond to incentives and to formulate a test of rational expectations. W concludes that participants perform poorly when trying to extract the information that is contained in previous actions and that rational expectations are violated in several systematic ways.

In this comment, we first show that the formulated test of rational expectations might generate false positives. The reason is that players with rational expectations assess the payoff of actions conditional on the true parameter values of the information structure, but the estimate of the payoff of actions presented in W relies on estimates of those parameters. Second, we report the results of regression analyses identical to those performed in W except that the estimate of the payoff of actions incorporates the true values of information parameters. We confirm that the rational expectations hypothesis is rejected, but we find that participants' biased tendency to follow own signal is less pronounced than suggested by W. The fraction of optimal choice earnings participants receive is comparable in situations where they should follow others and in situations where they should follow private information. Our improved measure of the success of social learning also indicates that participants make better inferences along equilibrium-path histories not because the public information is easy to interpret but because it is more valuable.

The remainder of the comment is organized as follows. In Section 2 we provide a decomposition of the empirical payoff of actions presented in W and we show that the formulated test of rational expectations might generate false positives. An alternative estimate of the payoff of actions straightforwardly derives from the decomposition. Section 3 measures the success of social learning in information cascade experiments based on the alternative estimate of the payoff of actions. We conclude with a few remarks in Section 4. All appendices can be found in the electronic supplementary material.

2 Empirical Payoff of Actions in Information Cascade Experiments

To facilitate the exposition of our results, we first provide some formal details about the considered class of information cascade games. Second, we report the main differences between the meta-dataset presented in W and our meta-dataset (henceforth the W and the ZMK meta-dataset, respectively). Third, we decompose the estimate of the (normalized) monetary payoff of actions presented in W which clarifies why testing rational expectations with the help of this estimate might generate false positives.

2.1 A Class of Information Cascade Games

In (almost) all information cascade experiments, participants interact repeatedly with each other and play a finitely repeated version of the cascade game. W assumes that, in any repetition of the stage game, players choose actions which are independent of history of play in previous repetitions. Players act as if their repeated interactions with other players were isolated interactions meaning that learning across repetitions as well as the prospect of future interactions are neglected. We therefore restrict our formal exposition to the one-shot version of the information cascade game.

There are two payoff-relevant states of Nature (henceforth states)—state $\mathcal{A}$ and state $\mathcal{B}$, and two possible actions—"predict state $\mathcal{A}$" simply denoted by A and "predict state $\mathcal{B}$" simply denoted by B. Nature chooses state $\mathcal{A}$ 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 S, with $\infty > \mid S \mid > 1$, and whose distribution depends on the state. Conditional on the state, private signals are independently distributed across players. In state $\mathcal{A}$ (resp. state $\mathcal{B}$), player n receives signal $s_n \in S$ with probability $0 < q_n(s_n \mid \mathcal{A}) < 1$ (resp. $0 < q_n(s_n \mid \mathcal{B}) < 1$) where $\sum_S q_n(s_n \mid \mathcal{A}) = \sum_S q_n(s_n \mid \mathcal{B}) = 1$. For each player n, the signal structure is a two-column matrix $Q_n \in \mathbb{Q}$ whose rows consist of two-element vectors $(q_n(s \mid \mathcal{A}), q_n(s \mid \mathcal{B}))$, with $s \in S$, 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 $h_t = ((a_1, Q_1), \ldots, (a_{t-1}, Q_{t-1})) \in H_t = \{\{A, B\} \times \mathbb{Q}\}^{t-1}$ where (a_τ, Q_τ) is the player's action and signal structure which is public in period $\tau \in \{1, \ldots, t-1\}$, and $h_1 = \emptyset$.

In Appendix A we derive the choice probabilities in quantal response equilibrium models assuming that, for all players, action A has vN-M payoffs $u(A, \mathcal{A}) = 1$ and $u(A, \mathcal{B}) = 0$, and action B has vN-M payoffs $u(B, \mathcal{A}) = 0$ and $u(B, \mathcal{B}) = 1$.

2.2 A New Meta-Dataset of Information Cascade Experiments

We compiled a new meta-dataset whose main differences with the W meta-dataset are as follows.[1]

On the one hand, the ZMK meta-dataset excludes the incomplete repetitions from Kübler and Weizsäcker (2004) (they amount to 242 observations), all 161 observations from Cipriani and Guarino (2005), and the 510 observations of one interrupted and two pilot sessions from Dominitz and Hung (2009). In the "no cost" treatment 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 obtain a signal. For the sake of simplicity, the theoretical choice probabilities of Section 2.3 are derived under the assumption that rationality incorporates an admissibility requirement—that is, the avoidance of weakly dominated strategies—in the additional stage. Accordingly, only repetitions where all six participants ask for a signal are included in our meta-dataset. Cipriani and Guarino (2005) implement a cascade game with three possible actions, so that assessing the extent to which participants respond to incentives requires knowledge about their risk attitudes. Since we do not possess this knowledge, we exclude the entire dataset. Data from early sessions with different experimental procedures as well as data from one disrupted session have been excluded from the statistical analysis in Dominitz and Hung (2009). We only include the 1,760 observations analyzed by Dominitz and Hung in our meta-dataset.

On the other hand, the ZMK meta-dataset includes all 1,440 observations from Ziegelmeyer, Koessler, Bracht, and Winter (2010) as well as the 1,080 individual observations from the PIT treatment of Fahr and Irlenbusch (2011).

Our meta-dataset contains a total of 30,683 decisions made by 2,948 participants in 13 information cascade experiments, and it shares approximately 95 percent of its content with the W meta-dataset.

[1] Though other differences between the two meta-datasets exist, they are minor. A more detailed account of how the ZMK meta-dataset has been built is available from the authors upon request.

Appendix B details the game structure of the experimental treatments contained in the ZMK meta-dataset.

2.3 Decomposition of the Empirical Payoff of Actions

We now describe how the empirical payoff of actions presented in W can be decomposed as a function of estimates of choice probabilities and estimates of the prior and signal qualities. For the sake of exposition, the decomposition displayed below does not take the A/B symmetry into account and we restrict ourselves to cascade games where $N = T$. Appendix C completes the description and provides the intermediate steps of the different decompositions.

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 participants' choices. Each row $1 \leq r \leq R$ comprises a vector of variable realizations that describe the participant's decision situation in the current period of a particular repetition of an experimental treatment.[2] An experimental treatment is characterized by the structure of the cascade game $\left(p, N, S, \{Q_n\}_{n=1}^{N}, T\right)$, 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. A repetition is characterized by a state of Nature $\omega \in \{\mathcal{A}, \mathcal{B}\}$ and a profile of signal realizations $\mathbf{s} = (s_1, s_2, \ldots, s_N) \in S^N$. In each period, the participant's decision situation additionally consists of the history $h \in \cup_{t=1}^{T} H_t$ observed by the participant and her chosen action $a \in \{A, B\}$.

Let $\mathfrak{R}(E, \omega, \mathbf{s}, h, a) = |\{1 \leq r \leq R \mid E_r = E, \omega_r = \omega, \mathbf{s}_r = \mathbf{s}, h_r = h, a_r = a,\}|$ denote the number of rows in the data matrix having E as experimental treatment, ω as state of Nature, $\mathbf{s}$ as signal realizations, h as history, and a as chosen action. In period $t \in T$ of treatment E where history $h_t \in H_t$ is observed and the signal realization of the player about to choose an action is $s_t \in S$, the estimated payoff of contradicting own signal presented in W is defined by

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

where $\mathbf{s}_{|s_t} \in S_{|s_t}^N$ is a profile of signal realizations such that the signal realization of the player deciding in period t is s_t, $a \in \{A, B\}$, $\omega \in \{\mathcal{A}, \mathcal{B}\}$, and $\mathbb{I}$ denotes the indicator function.

[2] Additional variable realizations not related to the decision situation—e.g. group or session IDs—facilitate the data analysis.

For a given treatment E, $mean\_pay \mid contradict(E, h_t, s_t)$ equals

$$\left[\left[1+\frac{(1-\hat{p})\,\widehat{\Pr}\left(s_t\mid\mathcal{B},h_t\right)}{\hat{p}\,\widehat{\Pr}\left(s_t\mid\mathcal{A},h_t\right)}\prod_{\tau<t}\frac{\sum_{s_\tau\in S}\widehat{\Pr}\left(s_\tau\mid\mathcal{B},h_\tau\right)\,\widehat{\Pr}\left(a_\tau\mid\mathcal{B},s_\tau,h_\tau\right)}{\sum_{s_\tau\in S}\widehat{\Pr}\left(s_\tau\mid\mathcal{A},h_\tau\right)\,\widehat{\Pr}\left(a_\tau\mid\mathcal{A},s_\tau,h_\tau\right)}\right]^{-1}\right]^{\mathbb{I}\left(\Pr(s_t|\mathcal{A})<\Pr(s_t|\mathcal{B})\right)}$$

$$*\left[\left[1+\frac{\hat{p}\,\widehat{\Pr}\left(s_t\mid\mathcal{A},h_t\right)}{(1-\hat{p})\,\widehat{\Pr}\left(s_t\mid\mathcal{B},h_t\right)}\prod_{\tau<t}\frac{\sum_{s_\tau\in S}\widehat{\Pr}\left(s_\tau\mid\mathcal{A},h_\tau\right)\,\widehat{\Pr}\left(a_\tau\mid\mathcal{A},s_\tau,h_\tau\right)}{\sum_{s_\tau\in S}\widehat{\Pr}\left(s_\tau\mid\mathcal{B},h_\tau\right)\,\widehat{\Pr}\left(a_\tau\mid\mathcal{B},s_\tau,h_\tau\right)}\right]^{-1}\right]^{\mathbb{I}\left(\Pr(s_t|\mathcal{A})>\Pr(s_t|\mathcal{B})\right)},$$

where $\hat{p}=\sum_a\sum_{\mathbf{s}}\mathfrak{R}\left(E,\mathcal{A},\mathbf{s},\emptyset,a\right)/\sum_\omega\sum_a\sum_{\mathbf{s}}\mathfrak{R}\left(E,\omega,\mathbf{s},\emptyset,a\right)$ is the consistent estimate of p in the first period, $\widehat{\Pr}\left(s_\rho\mid\omega,h_\rho\right)=\sum_a\sum_{\mathbf{s}_{|s_\rho}}\mathfrak{R}\left(E,\omega,\mathbf{s}_{|s_\rho},h_\rho,a\right)/\sum_a\sum_{\mathbf{s}}\mathfrak{R}\left(E,\omega,\mathbf{s},h_\rho,a\right)$ is the consistent estimate of $q_\rho\left(s_\rho\mid\omega\right)$ at history h_ρ with $\rho\in\{1,\ldots,T\}$, $\widehat{\Pr}\left(a_\tau\mid\omega,s_\tau,h_\tau\right)=\sum_{\mathbf{s}_{|s_\tau}}\mathfrak{R}\left(E,\omega,\mathbf{s}_{|s_\tau},h_\tau,a_\tau\right)/\sum_a\sum_{\mathbf{s}_{|s_\tau}}\mathfrak{R}\left(E,\omega,\mathbf{s}_{|s_\tau},h_\tau,a\right)$ is the consistent estimate of $\Pr\left(a_\tau\mid s_\tau,h_\tau\right)$ at state ω, and the empirical public likelihood ratio is assumed equal to one in the first period. Our decomposition shows that the accuracy with which the payoff of contradicting own signal is estimated in W not only depends on the accuracy with which choice probabilities are estimated, but it also depends on the accuracy with which the prior and signal qualities are estimated.[3] Accordingly, the larger the differences between estimates and true values of information parameters the less exact a measure of the success of social learning which is based on the empirical payoff of actions presented in W. Appendix D reports estimates of the prior and the signal qualities in the ZMK meta-dataset, the latter differing markedly from the true parameter values even at regular histories.

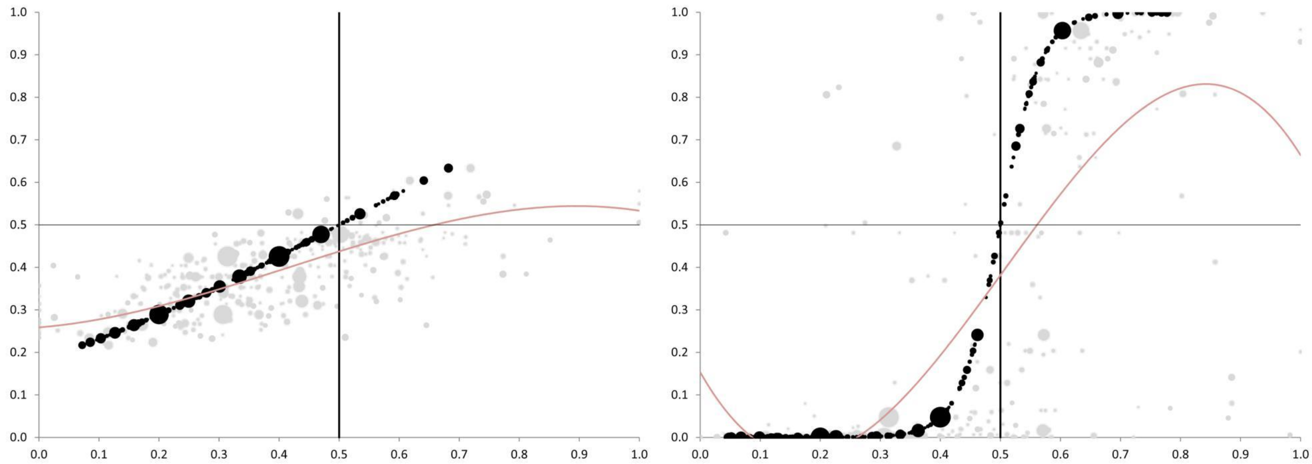
Another benefit of our decomposition is the suggestion of an alternative estimate of the payoff of contradicting own signal. For a given treatment E, the empirical payoff of contradicting own signal could incorporate the true parameter values of the prior and signal qualities in the underlying cascade game rather than their corresponding estimates. We refer to the former empirical payoff as the "*partial*" estimate of the payoff of contradicting own signal and to the latter empirical payoff as the "*full*" estimate of the payoff of contradicting own signal. Relying either on the *partial* or the *full* empirical payoff of actions to test rational expectations in information cascade experiments may produce divergent conclusions, as illustrated below.

Using the ZMK meta-dataset, we compute both estimates of the theoretical payoff of contradicting own signal where empirical choice probabilities are replaced with corresponding theoretical choice probabilities generated according to the logit quantal response equilibrium (LQRE).[4] Figure 1 plots the empirical payoff of contradicting own signal against the theoretical probability to contradict own signal for two values of the sensitivity to payoff differences ($\lambda = 1.5$ and 15). For each observation where $sitcount\left(E,h_t,s_t\right)=\sum_{\omega\in\{\mathcal{A},\mathcal{B}\}}\sum_{a\in\{A,B\}}\sum_{\mathbf{s}_{|s_t}}\mathfrak{R}\left(E,\omega,\mathbf{s}_{|s_t},h_t,a\right)>10$, each subfigure contains a black and a grey bubble. X-values of black and grey bubbles are given by the *partial* and *full* estimates of the payoff of contradicting own signal, respectively. Y-values of bubbles are given by the theoretical probabilities to contradict own signal associated with the pairs (h_t, s_t), and the size of bubbles reflects

[3]For example, the estimated payoff of contradicting own signal in the first period might be strictly greater than one-half for a given experimental treatment though according to the information structure of the underlying game following private information is always beneficial. Four experimental treatments contained both in the W and the ZMK meta-dataset produce such misleading estimates.

[4]In line with the notation of Appendix A and for a given $\lambda\geq 0$, $\widehat{\Pr}\left(a_\tau\mid\omega,s_\tau,h_\tau\right)$, $\tau\in\{1,\ldots,t-1\}$ and $\omega\in\{\mathcal{A},\mathcal{B}\}$, are replaced by the corresponding $\sigma^\lambda\left(a_\tau\mid s_\tau,h_\tau\right)$ for every triple (E,h_t,s_t) in the ZMK meta-dataset.

sitcount (E, h_t, s_t). In each subfigure, we add a red fitted line of a weighted OLS regression which includes an intercept, and linear, squared, and cubed terms of the *full* estimate of the payoff of contradicting own signal.



(a) $\lambda = 1.5$ (b) $\lambda = 15$

Note: 358 distinct values of (E, h_t, s_t) and 16,022 individual observations in total.

FIGURE 1: PROBABILITY TO CONTRADICT OWN SIGNAL IN LQRE

The *full* estimate of the payoff of contradicting own signal suggests that players in LQRE do not have a correct perception of the available information. Averaging across all observations where the *full* estimate is strictly greater than 1/2, the theoretical probability of optimal choice is 0.47 and 0.61 for $\lambda = 1.5$ and 15, respectively (for the complementary observations, the average theoretical probability of optimal choice is 0.65 and 0.94, respectively). Regression lines reach the level of one-half at *full* estimates of the payoff strictly greater than one-half (approximately 0.66 and 0.56 for $\lambda = 1.5$ and 15, respectively) giving the impression that players largely fail to contradict their signal when it is slightly beneficial to do so. In contrast, black bubbles are distributed along a symmetric S-shaped line which passes through (0.5, 0.5) since, for any triple (E, h_t, s_t), the *partial* estimate matches the theoretical payoff of contradicting own signal. For the sake of comparison, averaging across all observations where the *partial* estimate is strictly greater than 1/2, the theoretical probability of optimal choice is 0.56 and 0.88 for $\lambda = 1.5$ and 15, respectively (for the complementary observations, the average theoretical probability of optimal choice is 0.64 and 0.96, respectively).[5]

Players with rational expectations assess the payoff of actions conditional on the true values of information parameters not on their estimates. For this reason, using the *full* estimate of the payoff of actions to test rational expectations in information cascade experiments might generate false positives.

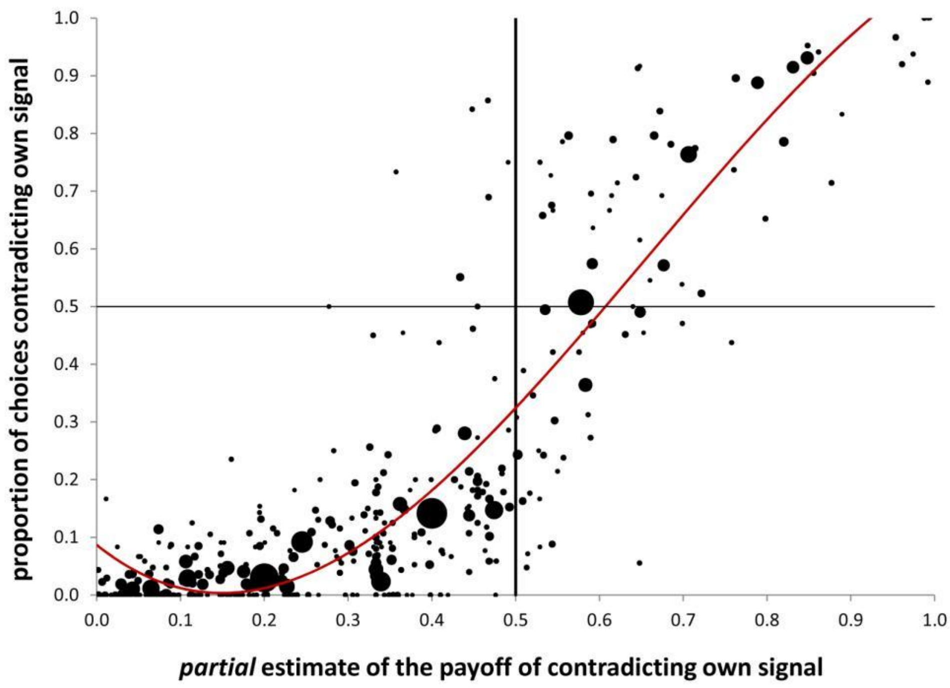
3 Improved Measure of the Success of Social Learning

The previous section shows that estimates of the payoff of actions in information cascade experiments should rely on the true values of the prior and signal qualities so that empirical choice probabilities are

[5]The inaccuracy of the *full* estimate of the payoff of actions is clearly reflected in its range. For each λ, the *full* estimate of the payoff of contradicting own signal takes any value between 0 and 1. Theoretical payoffs of contradicting own signal lie between 0.07 and 0.68 for $\lambda = 1.5$, and they lie between 0.05 and 0.78 for $\lambda = 15$.

the only source of sampling error. In this section, we report on statistical analyses identical to those described in W except that we use the *partial* estimate of the payoff of actions as a control variable and that we rely on the ZMK meta-dataset. In Appendix E we provide background information for the analyses and we also discuss the statistical results obtained by using the *full* estimate of the payoff of actions as a control variable. Appendix F replicates all analyses based on the W meta-dataset.

Figure 2 plots the *partial* estimate of the payoff of contradicting own signal against the proportion of choices contradicting own signal for observations where $sitcount\,(E, h_t, s_t) > 10$. Black bubbles have x-values given by *partial* estimates of the payoff of contradicting own signal, y-values given by associated proportions of choices contradicting own signal, and sizes which reflect $sitcount\,(E, h_t, s_t)$. The red line is the fitted line of a weighted OLS regression which includes an intercept, and linear, squared, and cubed terms of the *partial* estimate of the payoff of contradicting own signal.



Note: 358 distinct values of (E, h_t, s_t) and 16,022 individual observations in total.

FIGURE 2: Proportion of Contradicting Own Signal

The shape of the fitted line shows that on average participants do not optimally respond to the underlying incentives. For empirical payoffs slightly larger than 0.5, participants' choices cannot be best responses to rational expectations since the majority of choices should contradict own signal. This is confirmed by the rejection of the null hypothesis that the true correspondence between the payoff of contradicting own signal and its frequency goes through (0.5, 0.5) at any conventional level.[6] In line with W's qualitative findings, we observe that participants quite often fail to contradict their signal in decision situations where it is beneficial to do so though they (almost) always follow their signal in the complementary set of decision situations.

However, the systematic tendency of participants to follow their signal, relative to the benchmark of

[6]The hypothesis that participants exhibit a correct perception of the payoff of actions is also rejected when using an instrumental variable approach which addresses the measurement error problem. Details about the regression results and the statistical tests are to be found in Appendix E.

rational expectations, is less pronounced than suggested by W. The fitted line reaches the level of 0.5 at an empirical payoff of contradicting own signal equal to 0.61 whereas W reports a crossing payoff of 0.68. Additionally, 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 compared to W's reported frequency of 0.44 (for the observations in the left-half of the figure, the optimal choice occurs with a relative frequency of 0.92). Also in contrast with W, we find that participants leave comparable amounts of money on the table in situations where they should contradict their signal and in situations where they should follow their signal. Participants receive 0.87 and 0.93 of what they could have earned from making the optimal choice in the former and latter situations, respectively. We therefore conclude that participants are moderately successful in learning from others.

We also partially disagree with W's conclusions about the decision situations in which participants are disproportionately worse in making the correct inferences. On the one hand, we confirm that in decision situations where participants observe previous choices which contradict their signal their frequency of making the empirically optimal choice is significantly lower, even when the incentives are controlled for. On the other hand, we do not confirm that, holding incentives constant, participants are more successful in learning from others when the accumulated evidence from previous choices is strong and unambiguous. Our improved measure of the success of social learning indicates that participants make better inferences along equilibrium-path histories not because the public information is easy to interpret but because it is more valuable.

4 Concluding Remarks

The comment provides evidence against using the *full* estimate of the payoff of actions to test rational expectations in information cascade experiments. When relying on the true values of the prior and signal qualities to estimate the payoff of actions, we confirm W's finding that the rational expectations hypothesis is rejected. We also show that participants are moderately successful in learning from others and that the fraction of optimal choice earnings they receive is comparable in situations where they should follow others and in situations where they should follow private information.

W rightly concludes that estimating the payoff of actions and controlling for it in regressions that describe behavior can be used to test rational expectations in any experimental game. To ensure the validity of the test in experimental games with state uncertainty (e.g. experimental auctions or experimental stock markets), we claim that the empirical payoff of actions should incorporate the true parameter values of the information structure whenever the latter is public knowledge.

W also concludes that meta-analyses are well suited for testing rational expectations with the reduced-form approach. Though we agree that a meta-dataset comprises a large variety of decision situations, we note that estimates of the payoff of actions are computed at the treatment level. Since the empirical payoff of actions is measured with high precision only in treatments with many observations, either few studies are included in the analysis or large sampling errors are present. As a complement to meta-analyses, we argue in favor of experiments which allow participants to experience plenty of decision situations and generate a large dataset. Along these lines, March, Krügel, and Ziegelmeyer (2012) collect (almost) 20,000 observations to measure the success of social learning in a single information cascade experiment, and they observe that participants' biased tendency to follow own signal is almost non-existent.

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