Breakdowns in the Lab[*]

Johannes C. Hoelzemann[†] Nicolas Klein[‡]

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Abstract

We experimentally investigate a game of strategic experimentation in which information arrives through fully revealing, publicly observable, *breakdowns*. As predicted by theory, we find that players experiment significantly less, and payoffs are lower, when actions are unobservable. We view this as evidence that behavior is systematically affected by the informational environment and consistent with strategic free-riding.

JEL Classification: C73, C92, D83, O32

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[†]Universität Wien: www.johanneshoelzemann.com & jc.hoelzemann@gmail.com.

[‡]Université de Montréal: www.nicolasklein.com & kleinnic@yahoo.com.

1 Introduction

Gradual learning about the world is at the center of many economic decisions. For instance, it is well understood that learning is an important aspect in investment decisions in private assets (see, e.g., Sorensen 2008). The trade-off between exploitation vs. exploration, which, amongst others, is at the heart of venture-capital investment decisions, is canonically analyzed in the framework of the so-called bandit model (see e.g., Bergemann and Välimäki 2008). Bergemann and Hege (2005) analyzes the impact of feedback on incentives for an entrepreneur who receives financing from a venture capitalist and Krieger (2021) studies project continuation decisions where firms may resolve uncertainty through news about their own results and competitors' R&D failures.[1] In this paper, we provide experimental evidence showing that, in a strategic setting, transparency encourages investment. Rather than the relationship between investor and entrepreneur, this paper is concerned with the informational externalities between different private-asset investors. To isolate the informational dimension, we examine a setting with purely informational externalities, deviating from the contest framework employed by, e.g., Mihm and Schlapp (2019) and Halac, Kartik, and Liu (2017). In line with theoretical predictions, we find that unobservability of actions hurts effort provision with an uncertain technology if news arrives in the form of lumpy breakdowns.

Games of pure informational externalities have received a lot of attention in the literature (see, e.g., Bolton and Harris 1999, Keller, Rady, and Cripps 2005 or Hörner, Klein, and Rady 2022).[2] In these games, the information produced by a given player benefits other players as well—information is a public good, and players tend to produce inefficiently little of it in equilibrium. Following Keller, Rady, and Cripps (2005), most papers in this literature have focused on *breakthrough*, so-called good-news, environments, where discontinuous events bring good news; the absence of news consequently leads to a continuous deterioration in beliefs. In many real-world applications, however, discontinuous news events take the form of *breakdowns*, i.e., bad news; after all, a staggering 90% of all start-ups fail.[3] Such failure may well come about as

[1] Bergemann and Hege (1998), Manso (2011) and Klein (2016) also analyze incentive provision in a principal-agent setting; Ederer and Manso (2013) provide experimental evidence. Levinthal (1997), March (1991), Azoulay, Graff Zivin, and Manso (2011) study innovation search and examine what drives risky exploration among innovators.

[2] Wolitzky (2018) analyzes the trade-off between a safe and a risky option in the context of a continuum of short-lived players making decisions sequentially. For an application to political economics, see Callander and Harstad (2015) who analyze policy experimentation in federal systems.

[3] For up-to-date statistics, see, e.g., Kotashev (2024) and Howarth (2025).

a result of a sudden, singular, event, such as the discovery of severe side effects stemming from a medical drug, or the catastrophic malfunctioning of some technology. Theoretically, it is well understood (see, e.g., Keller and Rady 2015, or Achim and Klein 2022) that the mechanisms underlying the bad-news strategic-learning models differ sharply from those under good news. While Hoelzemann and Klein (2021) has experimentally investigated strategic experimentation under good news, and Hoelzemann, Manso, Nagaraj, and Tranchero (2024) investigates the role of players' information in a strategic setting with good news, we are, to the best of our knowledge, the first to experimentally investigate a bad-news strategic-experimentation setting. As predicted behavior contrasts sharply with that in breakthrough environments, we believe our investigation to be filling an important gap in the literature.

The scant attention given to settings with breakdowns is surprising because of their economic importance beyond investment choices and the financial world: Bad-news learning processes naturally occur upon the introduction of a new technology that holds out hopes of cost savings but entails risks. Such risky technologies include new drugs and medical devices, and innovative processes such as hydraulic fracturing for oil production. Some technologies that are socially undesirable, perhaps because they impose negative externalities on other sectors, also fit in this broad class. Consider financial fraud or tax evasion when agents have incomplete information about the effectiveness of the detection technology. In all these cases, there also exist significant barriers to the flow of information, making unobservable actions a good starting point for the analysis. For example, the decision to evade taxes is private, but getting caught is typically a public event.

In this paper, we are investigating in particular the role of the observability of actions in a bad-news game of strategic experimentation with bandits. These are games of purely informational externalities, where players have an incentive to free-ride on the information produced by the other players. In a continuous-time, infinite-horizon, setting, it is theoretically known that, in a conclusive bad-news model, unobservable actions tend to be bad for welfare (Bonatti and Hörner 2017). This is because, in the absence of conclusive news, observing a player's shirking in information production makes the other player(s) more pessimistic than they would be on the equilibrium path if the conclusive bad news fails to materialize. Therefore, with conclusive bad news, players will be less prone to slack off in information production if their actions are observable, because, after observing a deviation, the other player(s) will be warier about the risky option than they would be absent a deviation. Because the only externality in the game is the positive informational externality between players, leading to a tendency toward under-production of information in equilibrium, we should expect that making deviations unobservable ought to dampen welfare in a conclusive bad-news environment.

The main goal of this investigation is to test whether this qualitative prediction of the theory is borne out by actual behavior in a controlled laboratory environment. Empirically, we indeed find that both experimentation and payoffs are higher with observable actions, as predicted by theory. We have constructed our game in a particularly stark way so that it has the feature that the efficient solution is an equilibrium *if and only if* actions are observable. Further, participants use the risky option more frequently over time, consistent with the growing optimism predicted after histories without breakdowns.

In summary, the paper makes two main contributions. First, we present evidence that, in a *bad-news* setting, behavior is systematically affected by the informational environment. We find that both experimentation and payoffs are *higher* with observable actions. Second, behavior is consistent with strategic free-riding, as information is a public good and participants produce inefficiently little of it. Participants experiment, on average, too little even when the efficient solution is an equilibrium.

We close the introduction by situating the paper within the related theoretical and experimental literature on strategic experimentation.

Related Literature

Our theoretical framework can be viewed as a model of experimentation. Initially, the literature focussed on the trade-off of an individual decision maker who acts in isolation. Bolton and Harris (1999) and Keller, Rady, and Cripps (2005) have extended the individual decision problem to a multi-player framework. Since then this literature is steadily growing. For example, Klein and Rady (2011), Klein (2013), and Hörner, Klein, and Rady (2022) study various bandit problems in which different players may choose different arms. While free-riding is a central element in these studies as well, players' actions are observable. Several studies analyzed experimentation in teams where the outcome of each player's action is unobservable while their actions are observable (Rosenberg, Solan, and Vieille 2007, Murto and Välimäki 2011, Hopenhayn and Squintani 2011), while Bonatti and Hörner (2011) studies the case of observable outcomes with unobservable actions. In particular, Keller and Rady (2015) study the bad-news setting under observable actions, while, closest to our setting, Bonatti and

Hörner (2017) study a bad-news setting where actions are not observed but outcomes are.

Our paper is embedded in an emerging literature that studies behavior in experiments of experimentation with breakthrough-learning in groups; that is, multi-player settings with strategic links across players where decision-makers are *not* acting in isolation *and* informational externalities exist. We are aware of only four other experimental investigations of good-news strategic-experimentation problems with bandits. Hoelzemann and Klein (2021) experimentally implement a dynamic public-good problem where information about agents' common state of the world is dynamically evolving. Observed behavior is consistent with free-riding because of strategic concerns, and participants adopt non-cut-off behavior and frequent switches of action. Boyce, Bruner, and McKee (2016) study a setting with ambiguity concerning the type of the risky arm to test strategic free-riding in a two-player, two-period, game. Players are asymmetric in their costs in that one player was known to have lower opportunity costs for playing risky than the other, so that it was clear which player ought to play the free-rider in the first period. Von Essen, Huysentruyt, and Miettinen (2020) implement a treasure-hunt game in the laboratory, finding that the information externality can induce an encouragement effect. Hoelzemann, Manso, Nagaraj, and Tranchero (2024) study an environment where players must explore across different options with varying but uncertain payoffs. While informative signals, interpreted as data, can typically reduce uncertainty and improve welfare, in their setting it can instead decrease individual and group payoffs. When data highlights sufficiently attractive but dominated options, it can crowd-out exploration and thus lower payoffs as compared to when no data is provided. Importantly, empirical evidence from the field of genetics research provides a real-world confirmation of their framework and shows that data on genetic targets of medium promise can significantly increase the delay of valuable discoveries.

By contrast, this paper provides the first experimental investigation of breakdown-learning in a strategic setting.

2 The Environment

We have endeavored to come up with the simplest possible environment in which theory would predict lower welfare with unobservable actions. For the effect to arise, we need at least three periods. This is because, in the last period, a player does not care what their opponent will do, as they have no future use for the information learned in this period. So, only in the first period do players want to alter their opponent's future behavior for strategic considerations. We therefore construct a three-period, two-player, simultaneous-move game, calibrating the parameters in such a way that the game features the strategic effects we are interested in. The efficient solution has both players using the risky option in all periods (absent a breakdown); the unique equilibrium with unobservable actions has both players never using the risky option, while either always or never playing risky are the two equilibria with observable actions.

Specifically, there are two risk-neutral players, and the game is played over three periods $t = 1, 2, 3$. In each period, players make a simultaneous choice. At the end of the period, outcomes are revealed; we vary whether a player's choice is observable. If the safe arm is used, the payoff will be 0 for certain in that period. Using the risky arm entails a *benefit* of $s = 2857$. The risky arm is either *good* or *bad*, its type remaining constant over the three periods of the game. If it is good, its use never imposes a cost. If it is bad, it leads to a breakdown, imposing a cost of 20000, with a probability of $\lambda = 0.25$ in any period it is used. Conditionally on the risky arm's type, the draws are i.i.d. between players and across periods; there are thus no payoff externalities between the players, as only the player whose arm incurs the breakdown bears its cost. Players do not initially know if the risky arm is good or bad; they know that Nature (or the computer) makes the risky arm bad with a probability of $p_0 = 0.676$. After a breakdown is observed, the risky arm is known to be bad with probability 1. In the absence of a breakdown and n successful tries of the risky arm, Bayes' rule implies that an observer knowing this information should hold the belief $p_n = \frac{p_0(1-\lambda)^n}{p_0(1-\lambda)^n+1-p_0}$ that the risky arm is bad; i.e., observing that the risky arm has been used without a breakdown makes players increasingly *optimistic* about the quality of the risky arm. Thus, the updated posterior belief either jumps to 1 in case of a breakdown, or declines with the number of unsuccessful tries n. Arm types are i.i.d. across games. One player's risky arm is good *if and only if* the other one's is as well. In the treatment with *observable* actions, a player observes all of the other player's previous actions as well as the outcomes of these actions. In the treatment with *unobservable* actions, a player observes only if the other player has suffered a breakdown of 20000 from the risky arm or not.

More formally, the solution concept is that of pure-strategy perfect Bayesian equilibrium.[4] Sequential rationality is verified by moving backwards in time. After a breakdown has been publicly observed, the risky arm is known to be bad, so that playing safe is the dominant action. Subsequently, we thus verify sequential rationality conditionally on no breakdown having been observed. We normalize the cost of a breakdown to 1.[5] We write $p_i(t) \equiv p_n$ for player i's Bayesian belief in period $t \in \{1, 2, 3\}$, if $n = \sum_{z=1}^{t-1}(k_{i,z} + \hat{k}_{-i,z})$, where we write $k_{q,z} = 1$ ($k_{q,z} = 0$) if player $q \in \{i, -i\}$ has used the risky (safe) arm in period z without suffering a breakdown, and $\hat{k}_{-i,z}$ denotes the action that player i thinks that player $-i$ has taken in period z. In the case of observable actions, $\hat{k}_{-i,z} \equiv k_{-i,z}$; in the case of unobservable actions, $\hat{k}_{-i,z}$ is pinned down by player i's expectations, which are correct in equilibrium.

In the last period $t = 3$, players face a myopic decision problem, where playing risky is a best response *if and only if* $p(t = 3)\lambda \leq s$. For our parameters, $p_n\lambda < s$ *if and only if* $n \geq 2$.

Indeed, $p_2\lambda < s$ implies that, after a history of two tries without a breakdown, playing risky becomes a dominant action. This pins down play in all equilibrium candidates in which $k_{i,1} + k_{-i,1} = 2$.

Now, let us assume that $k_{i,1} + k_{-i,1} = 1$. Suppose that $k_{-i,2} = 1$ (so that $k_{i,3} + k_{-i,3} = 2$). In this case, $k_{i,2} = 1$ is a best response *if and only if*

$$s - p_1\lambda + \left(1 - p_1 + p_1(1-\lambda)^2\right)s - p_1\lambda(1-\lambda)^2 \geq \left(1 - p_1 + p_1(1-\lambda)\right)s - p_1\lambda(1-\lambda)$$

$$\iff p_1 \leq \frac{s}{\lambda}\frac{1}{1-(1-\lambda)(\lambda - s)},$$

which holds for our parameters. Thus, $k_{i,2} = 1$ is a best response to $k_{-i,2} = 1$.

Next, let us assume that $k_{-i,2} = 0$. If actions are observable, $k_{i,2} = 1$ will induce $k_{i,3} + k_{-i,3} = 2$, and $k_{i,2} = 0$ will induce $k_{i,3} = k_{-i,3} = 0$. Thus, $k_{i,2} = 1$ is a best response *if and only if*

$$s - p_1\lambda + (1 - p_1\lambda)s - p_1\lambda(1-\lambda) \geq 0$$

$$\iff p_1 \leq \frac{s}{\lambda}\frac{2}{2-(\lambda - s)},$$

which is not satisfied for our parameters. Thus, $k_{i,2} = 0$ is the unique best response to $k_{-i,2} = 0$ if actions are observable, inducing $k_{i,3} = k_{-i,3} = 0$. Now suppose that actions

[4] Subgame perfection has no bite as an equilibrium refinement, because the game starts with an initial move of Nature, which determines the quality of the risky arm; the game therefore admits of no proper subgames.

[5] For our parameters, this implies that $s = 2857/20000 = 0.14285$. Recall furthermore that $\lambda = 0.25$, and $p_0 = 0.676$.

are unobservable. We have already shown that $k_{i,2} = 1$ (inducing $k_{i,3} = k_{-i,3} = 1$) cannot happen on the equilibrium path. Now, $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$ can be part of an equilibrium *if and only if*

$$0 \geq s - p_1\lambda + (1 - p_1\lambda)s - p_1\lambda(1 - \lambda)$$

$$\iff p_1 \geq \frac{s}{\lambda}\frac{2}{2 - (\lambda - s)},$$

which is satisfied for our parameters, as we have seen.

Thus, in conclusion, after a history such that $k_{i,1}+k_{-i,1} = 1$, both $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$ and $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 1$ are compatible with equilibrium, whether actions are observable or unobservable. It is this non-uniqueness of equilibrium play after histories $k_{i,1} + k_{-i,1} = 1$ that will lead to different first-period equilibrium predictions depending on whether actions are observable or unobservable, as we shall see below.

Let us turn to histories such that $k_{i,1} = k_{-i,1} = 0$. Clearly, $k_{-i,2} = k_{i,3} = k_{-i,3} = 0$, while $k_{i,2} = 1$ is not compatible with equilibrium, because $s - p_0\lambda < 0$ implies that i has an incentive to deviate to $k_{i,2} = 0$. Can $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 1$ occur in equilibrium? If actions are observable (unobservable), a deviation by player i in $t = 2$ leads to a path of play of $k_{i,2} = k_{i,3} = k_{-i,3} = 0$, with $k_{-i,2} = 1$ ($k_{i,2} = k_{i,3} = 0$, with $k_{-i,2} = k_{-i,3} = 1$), giving the deviator i a payoff of 0 in both cases; such a deviation is therefore profitable *if and only if*

$$0 > s - p_0 + \left(1 - p_0 + p_0(1 - \lambda)^2\right)s - p_0(1 - \lambda)^2\lambda$$

$$\iff p_0 > \frac{s}{\lambda}\frac{2}{1 + s(2 - \lambda) + (1 - \lambda)^2},$$

which holds for our parameters. The only equilibrium candidate remaining is thus $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$; this clearly is compatible with equilibrium as $s - p_0\lambda < 0$.

Let us now move to the first period $t = 1$, and assume that actions are observable. By our previous analysis, there are four equilibrium candidates: (1.) the utilitarian optimum, namely $k_{i,1} = k_{-i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 1$, (2.) $k_{i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 1$ and $k_{-i,1} = 0$, (3.) $k_{i,1} = k_{-i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$, and (4.) $k_{-i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$, while $k_{i,1} = 1$. Candidate (4.) can be ruled out right away, as $s - p_0\lambda < 0$, so that player i has an incentive to deviate in the first period, whether actions are observable or unobservable.

Let us turn to candidate (1.). With observable actions, a unilateral deviation by i

in the first period can be "punished" with the continuation equilibrium $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$, making the deviation unprofitable; indeed, in the absence of a deviation, players get the utilitarian optimum, which is strictly greater than 0, whereas, by deviating, i receives 0. For unobservable actions, however, this "punishment equilibrium" is not available, and (1.) is an equilibrium *if and only if*

$$s - p_0\lambda - 2p_0\lambda(1-\lambda)s + p_0\lambda(1-\lambda)(s+\lambda) + p_0\lambda(1-\lambda)^3(\lambda - s) \geq 0$$

$$\iff p_0\lambda\big[1 - (1-\lambda)(\lambda - s)\big(1 + (1-\lambda)^2\big)\big] \leq s,$$

which is violated for our parameters. Therefore, the utilitarian optimum (1.) is an equilibrium *if and only if* actions are observable.

Next, let us analyze candidate (2.). If actions are observable (unobservable), a first-period deviation by player i who is supposed to play risky in that period leads to play of $k_{i,1} = k_{-i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$ ($k_{i,1} = k_{-i,1} = k_{i,2} = k_{i,3} = 0$, with $k_{-i,2} = k_{-i,3} = 1$). In either case, this deviation is profitable *if and only if*

$$0 > s - p_0\lambda + (1 - p_0\lambda)s - p_0(1-\lambda)\lambda + \big(1 - p_0 + p_0(1-\lambda)^3\big)s - p_0(1-\lambda)^3\lambda,$$

which holds for our parameters. Thus, candidate (2.) is eliminated, whether actions be observable or unobservable.

Finally, let us turn to candidate (3.). If actions are observable, a first-period deviation leads to play of either $k_{i,1} = 1$, with $k_{-i,1} = k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$ or $k_{-i,1} = 0$ with $k_{i,2} = k_{-i,2} = k_{i,3} = k_{-i,3} = 0$. In the latter case, the deviation is unprofitable as $s - p_0\lambda < 0$; in the former, it is unprofitable by the same argument as in the previous paragraph. With unobservable actions, deviating in only one period is unprofitable as $s - p_0\lambda < 0$. A deviation to $k_{i,1} = k_{i,2} = k_{i,3} = 1$ is profitable *if and only if*

$$0 < s - p_0\lambda + \big(1 - p_0 + p_0(1-\lambda)\big)\big[s - p_1\lambda + \big(1 - p_1 + p_1(1-\lambda)\big)s - p_1(1-\lambda)\lambda\big].$$

Yet, $s - p_0\lambda < 0$, and, as we have shown above, $s - p_1\lambda + \big(1 - p_1 + p_1(1-\lambda)\big)s - p_1(1-\lambda)\lambda < 0$. We thus conclude that candidate (3.) is an equilibrium, whether actions be observable or unobservable.

We summarize our findings in the following

Proposition 1. *If actions are unobservable, players uniquely always play safe in perfect Bayesian equilibrium. This remains an equilibrium with observable actions. With ob-*

servable actions, the utilitarian optimum (in which players play risky until a breakdown arrives) is an additional equilibrium, which is supported by the threat of always playing safe in case of a deviation.

We summarize the equilibrium implications and the behavioral predictions that guide the empirical analysis in Table I.

Table I: Theoretical Implications and Behavioral Predictions by Action Observability

	Observable Actions	Unobservable Actions
Equilibrium set	Two equilibria: efficient risky play until a breakdown; always safe.	Unique equilibrium: always safe.
Efficient outcome	Supportable by the threat of reverting to always safe after a deviation.	Not supportable, since deviations are not observed.
Behavioral prediction	Higher experimentation and payoffs if participants coordinate partly on the efficient equilibrium.	Lower experimentation and payoffs due to strategic free-riding.
Dynamics after no breakdown	After histories without breakdowns, the risky arm becomes more attractive; hence risky play is predicted to weakly increase over time in both treatments.	

Implications for Behavior Consequently, we hypothesize that action observability matters. Our behavioral hypotheses are as follows:

- We observe efficient behavior more often with observable than with unobservable actions.
- Participants use the risky arm *more* when actions are observable.
- Participants' payoffs are *higher* when actions are observable.

Since players' beliefs are (weakly) increasing over time in the absence of breakdowns, their myopic payoff from playing risky is (weakly) increasing over time conditionally on no breakdown occurring. That is, not playing risky becomes more costly over time. We therefore also want to test whether participants use the risky arm *more* in later periods.

3 The Experiment

3.1 Organization

We conducted all experiments in the months of July to November 2023 at the University of Vienna. Participants were recruited from the Vienna Center for Experimental Economics (VCEE) subject pool using ORSEE (Greiner 2015). No one participated in more than one session. During the experiments, participants could contact an experimenter anytime for assistance. After reading the instructions, participants had to correctly answer several comprehension questions before starting the main part of the experiment. The experiment was programmed in oTree (Chen, Schonger, and Wickens 2016). We recruited 104 participants, with an average of 13 participants per session. Each treatment had 52 participants. Participants received a €10 show-up fee. In addition, one randomly selected game determined the variable part of the payment, which could be positive or negative because breakdowns generated losses. Participants earned on average approximately €10.57 in total, with a standard deviation of €8.48. All payments were made in cash and in euros, using a conversion rate of 1000 points = €1. The instructions and experimental interface are reproduced in the Supplemental Appendix.

3.2 Implementation

In order to increase the computational efficiency of the implementation and to increase control, we had simulated all the relevant parameters ahead of time. As all our stochastic processes are Bernoulli processes, simulating their realizations ahead of time is equivalent to simulating them as the game progresses. These included separate processes for the quality of the risky arm and the timing of breakdowns on the risky arm in case it was bad.[6] We generated 25 different sets of realizations of the random parameters controlling the quality of the risky arm and the arrivals of the bad risky arm. These corresponded to 25 different games that each of our participants played. To make our findings more easily comparable, we have kept the same realizations for both observable and unobservable actions. Participants were randomly assigned to groups of two players and randomly rematched within a matching group of six to eight participants after each game. Each participant was randomly assigned either to the treatment with observable or unobservable actions, and played the 25

[6] Details are available upon request.

games in random order. To ensure a balanced data-collection process, we replicated any order of the 25 games that was used for a matching group in the treatment with observable actions for a matching group in the treatment with unobservable actions.

As illustrated in Figure 1, in the treatment with observable actions, participants could see their opponent's as well as their own past action choices and payoffs. In the treatment with unobservable actions, participants could see only if, and when, their opponent had suffered a breakdown so far as well as their own past action choices and payoffs.[7,8]

4 Findings

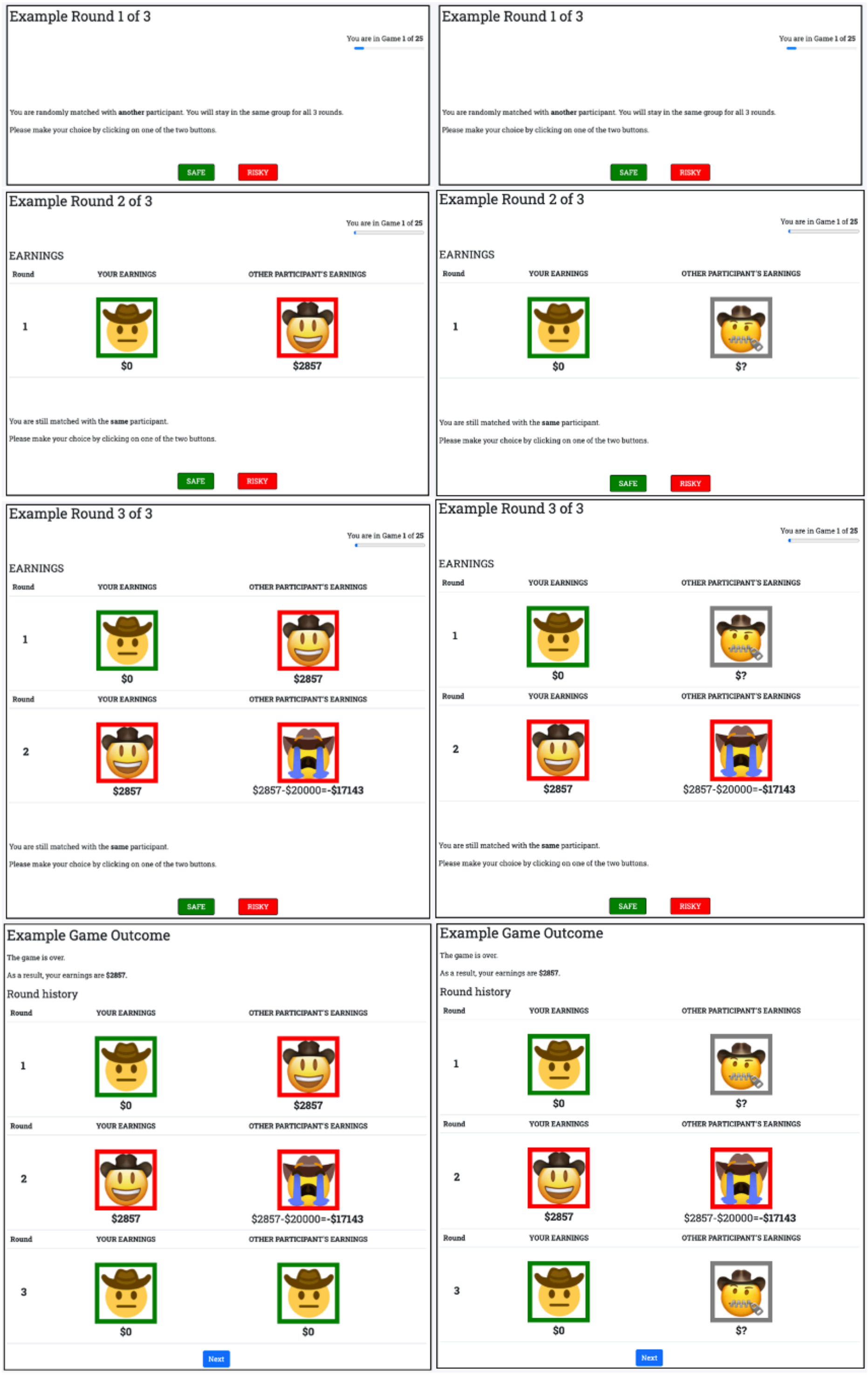
This section is dedicated to examining the implications for behavior as detailed in Section 2. For each of the 25 games, we implemented two treatments, with observable and unobservable actions respectively, within two-player groups, comprising 52 groups in total. These groups were randomly re-matched within a matching group after each game. We organize the analysis as follows. We first present summary statistics, highlighting both the average intensity of experimentation, $\frac{1}{3}\sum_{t=1}^{3}\frac{k_{1,t}+k_{2,t}}{2}$, where $k_{i,t} = 1$ if player i played risky in period t and $k_{i,t} = 0$ otherwise, and the overall group payoffs. Following this, we examine the aggregate experimental outcomes, with an initial focus on the distribution of experimentation intensities and group payoffs. We then assess efficiency by comparing observed behavior to the theoretical efficient solution, study how behavior relates to our equilibrium predictions, and examine the dynamic evolution of behavior within games. Finally, we analyze history dependence in risky play, heterogeneity in experimentation behavior, and the robustness of the main treatment effects.

4.1 Experimentation and Payoffs

As outlined in Section 2, we anticipate that average experimentation intensity and group payoffs will be higher when actions are observable. We measure experimen-

[7]Screenshots can be found in the Supplemental Appendix.

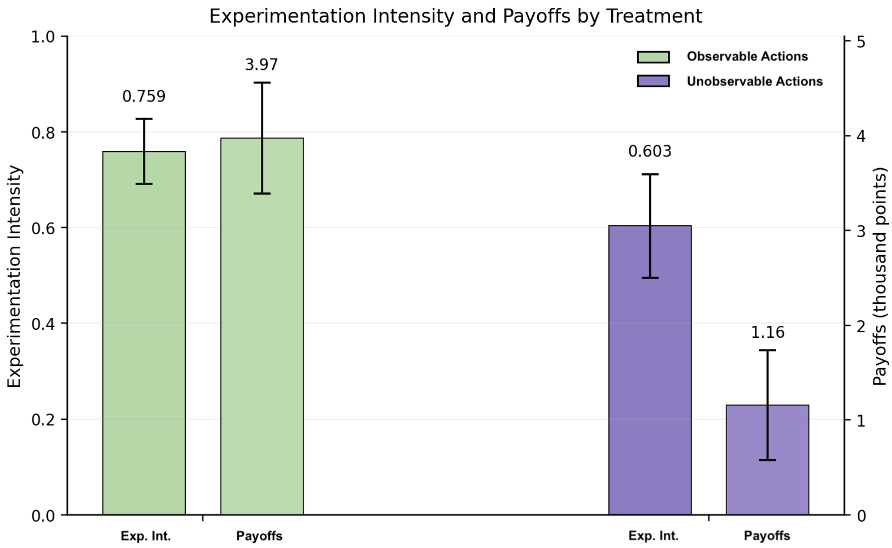
[8]We did not elicit beliefs, risk preferences, or altruism. This was a deliberate design choice to keep the experiment focused on the strategic experimentation task. In addition, prior studies in similar bandit environments with good news did not detect a statistically significant effect of risk preferences on behavior (Hoelzemann and Klein 2021; Hoelzemann, Manso, Nagaraj, and Tranchero 2024; or Hudja and Woods 2025). We therefore interpret our history-dependence results below as revealed-choice evidence on how participants condition behavior on available histories, rather than as direct evidence on belief updating.



Left: The *Observable Actions* treatment; right: The *Unobservable Actions* treatment.

Figure 1: Experimental Implementation

tation intensity for each player up until the moment a first breakdown occurs to any player in the group. Figure 2 presents the observed mean experimentation intensities and average total payoffs by action observability.



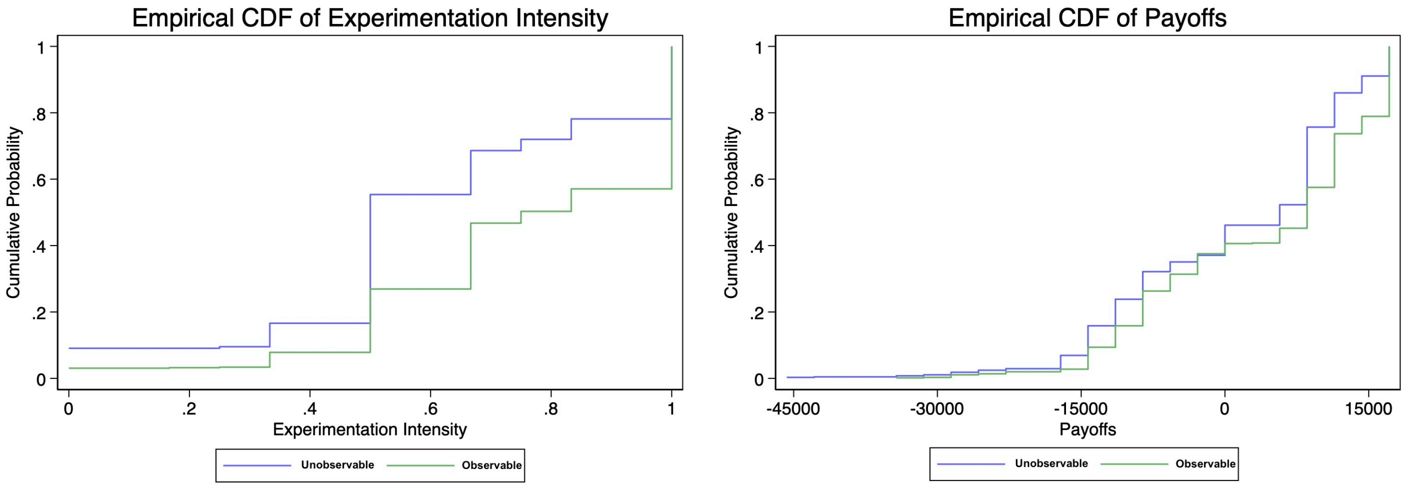
The figure reports mean experimentation intensity and mean payoffs by action observability. Payoffs are shown in thousand points. Error bars indicate 95% confidence intervals based on standard errors clustered at the matching-group level.

Figure 2: Experimentation Intensity and Payoffs by Action Observability

The figure shows pronounced positive treatment differences for both outcomes. In OLS treatment-difference regressions with standard errors clustered at the matching-group level, observable actions increase experimentation intensity by 0.156 (s.e. 0.031, $p < 0.001$) and group payoffs by 2,813 (s.e. 319, $p < 0.001$). Participants therefore pull the risky arm considerably more often when actions are observable, and this translates into markedly higher group payoffs.

Figure 3 illustrates the empirical distribution of experimentation intensities and group payoffs across the different treatments.

As can be seen in Figure 3, the empirical distribution functions for both experimentation intensity and group payoffs lie everywhere weakly below the corresponding distributions under unobservable actions. Thus, the sample distributions are consistent with first-order stochastic dominance of observable actions over unobservable actions for both outcomes. Formal Barrett–Donald tests of first-order stochastic dominance do not reject dominance of observable actions over unobservable actions for either outcome, while rejecting the reverse dominance relation for both experimen-



The sample cumulative distribution functions for experimentation intensity and payoffs are shown, by action observability.

Figure 3: Empirical CDFs of Experimentation Intensities and Payoffs

tation intensity and payoffs.[9]

We summarize these findings in the following:

Experimentation Participants use the risky arm *more* when actions are observable.

Payoffs Group payoffs are *higher* when actions are observable.

That participants should use the risky arm more with observable actions is consistent with the (larger) equilibrium set, unless one expected for some reason that the equilibrium in which everyone plays safe all the time was the only equilibrium being played. In particular, note that there is a stark difference in first-round experimentation intensities, see Figure 5, an effect that cannot be accounted for by channels other than the strategic forces related to action observability.

To rule out that our results are driven by noisy behavior, as a robustness test, we focus only on games in which at least one breakdown occurred and all players behaved optimally thereafter by playing safe. This is the case in approximately 68% of games with a breakdown. Equivalently, in 31.9% of games with a breakdown, at least one player chose the risky arm after a breakdown had already occurred. At the player-period level, participants chose risky after a previous breakdown in 30.0% of such

[9]For the null that observable actions first-order stochastically dominate unobservable actions, the Barrett–Donald test statistic is 0.000 for both experimentation intensity and payoffs, with bootstrap p-values of 1.000. For the reverse dominance relation, the corresponding test statistics are 5.131 for experimentation intensity and 3.384 for payoffs, with bootstrap $p < 0.001$ in both cases.

observations, with a rate of 35.4% under observable actions and 24.4% under unobservable actions. In this restricted sample of games with optimal post-breakdown behavior, both experimentation intensity and payoffs remain higher when actions are observable, and these differences are also highly significant, with p-values of 0.001.

4.2 Efficiency Benchmark

To assess the efficiency of participants' behavior, our analysis concentrates on games where no breakdown was suffered during the three interaction periods. In the treatment where actions are observable, the average experimentation intensity stands at 0.762 (with a standard deviation of 0.253, N=312), significantly deviating from the theoretical efficient solution of 1. Out of 312 observations, 136 are in alignment with the efficient solution. Conversely, for games with unobservable actions, the average experimentation intensity with 0.592 and a standard deviation of 0.280 for N=312 is also significantly different from the efficient solution, and only 57 of 312 observations directly coincide with the efficient solution.

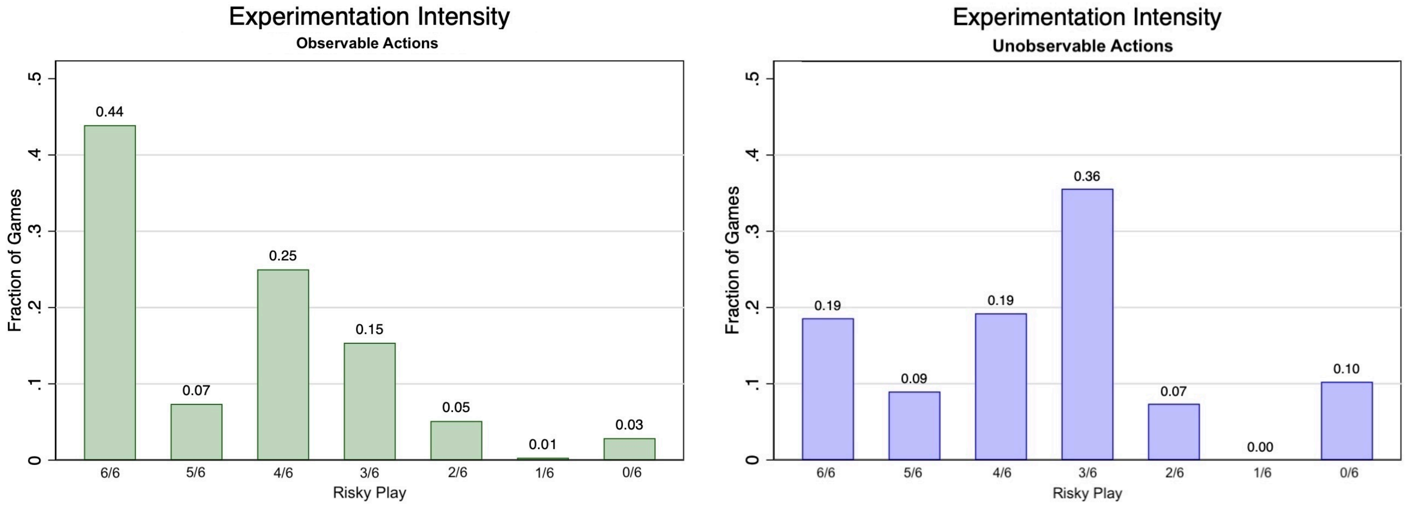
Efficiency Participants free-ride, i.e., they use the risky arm *less* than what would be efficient with either observable or unobservable actions.

4.3 Consistency of Behavior with Equilibrium

Here too, our analysis focuses on the 312 games where no breakdown was suffered during the three interaction periods. In Figure 4, we highlight the observed risky play for each treatment separately, providing a detailed view of how behavior is associated with equilibrium play. In particular, we plot the fraction of games in which risky was played r times divided by the number of periods t multiplied by the number of players n, i.e., $\frac{r}{t \times n}$.

When actions are observable, 144 of 312 games are consistent with equilibrium; among these, the overwhelming majority, namely 136 games, coincide with the efficient solution. By contrast, with unobservable actions, play that is consistent with the—now smaller—equilibrium set significantly decreases, with only 32 of 312 in line with the theoretical prediction. Unsurprisingly, the difference in equilibrium play by treatment is highly statistically significant with p-values of 0.001 for both a t-test and a two-sided Wilcoxon rank-sum test.

This leads to the following:



The experimentation intensity in games without breakdowns is shown, by action observability.

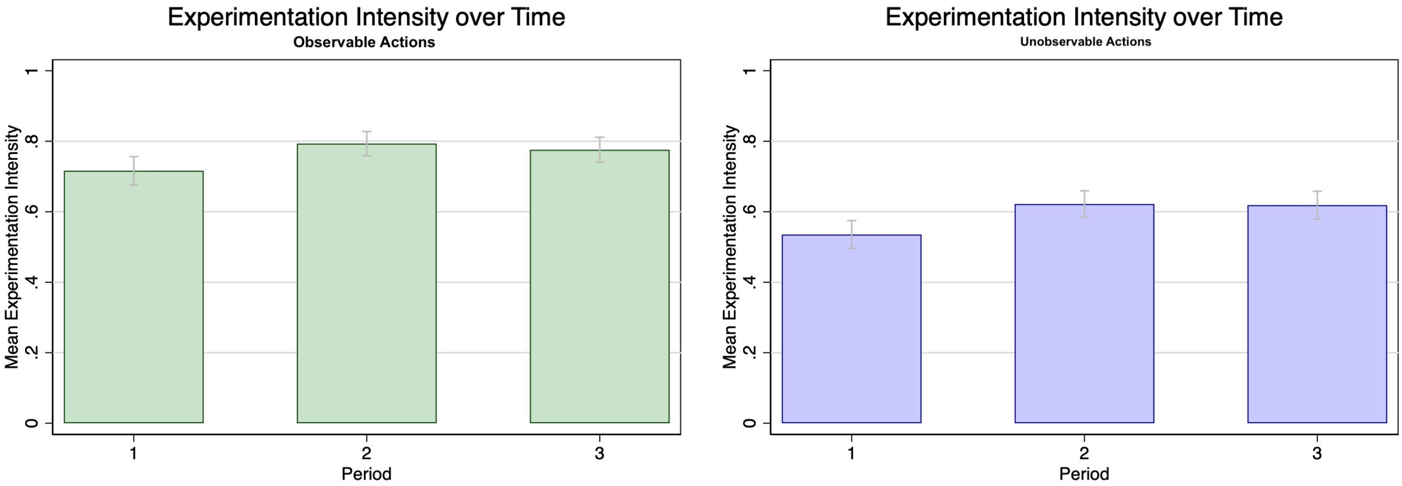
Figure 4: Experimentation Intensities

Equilibrium Behavior is more often consistent with equilibrium when actions are observable.

4.4 Dynamic Evolution of Behavior

We now shift our focus to the dynamics of observed behavior. We are particularly interested in whether participants increase their use of the risky arm as the game progresses. Our attention remains on games where no breakdown is incurred throughout the three periods of interaction. In Figure 5, we graph the observed experimentation intensities for each period and treatment separately, providing a detailed view of how behavior evolves over the course of the game.

While it is unrealistic to expect our participants to calculate posterior beliefs precisely using Bayes' rule, we nevertheless anticipate that, in the absence of a breakdown, participants will increasingly use the risky arm as the game progresses, reflecting growing optimism. At the beginning of a game without any breakdowns, participants are indeed significantly less likely to choose the risky arm than in later periods. To examine changes in behavior over time, we employ two-sided t-tests for parametric analysis and two-sided Wilcoxon rank-sum (Mann-Whitney) tests for non-parametric analysis, treating group averages as independent observations. Regardless of whether actions were observable, we find that the differences in experimentation intensities across time are highly statistically significant when comparing behavior in



The average experimentation intensity over time in games without breakdowns is shown, by action observability.

Figure 5: Experimentation Intensities over Time

the first period to that in either the second or the last period. In the treatment with observable actions, t-tests (two-sided Wilcoxon rank-sum tests) produce p-values of $p_{12} = 0.012$ (0.024), $p_{13} = 0.089$ (0.121), and $p_{23} = 0.411$ (0.480), where $p_{\alpha\beta}$ is the p-value when comparing periods α and β. With unobservable actions, by contrast, we find p-values of $p_{12} = 0.001$ (0.002), $p_{13} = 0.008$ (0.007), and $p_{23} = 0.643$ (0.751), respectively.

Additionally, we also analyze mean experimentation intensities across treatments for each period. Participants engage with the risky arm more frequently when actions are observable. The differences in all periods are highly statistically significant, with p-values of 0.001 for both tests.

To assess whether the treatment difference is driven primarily by initial behavior or by differential evolution across rounds, we also compare treatment differences period by period. In games without breakdowns, experimentation is higher when actions are observable in every period. The treatment difference is already pronounced in period 1: experimentation intensity is 0.724 under observable actions and 0.538 under unobservable actions, a difference of 0.186. The corresponding differences are 0.165 in period 2 and 0.157 in period 3. Thus, the treatment effect is not driven mainly by divergent behavior over the course of the game; rather, a substantial gap is present from the first period and persists throughout the interaction. This is important because the first-period difference cannot be attributed to within-game learning from previous outcomes or actions. Instead, it is consistent with the strategic effect of action observability operating already at the start of the game.

We obtain the same conclusion from a linear probability model in which risky play is regressed on the observable-actions treatment indicator, period indicators, and interactions between observable actions and the period indicators. In this specification, the observable-actions coefficient captures the treatment difference in period 1, while the interaction terms capture whether the treatment difference changes in periods 2 and 3. The observable-actions coefficient is positive and statistically significant, whereas the interaction terms are small and not statistically significant. Hence, the treatment difference is already present in the first period and does not appear to be driven by differential evolution across periods.

We summarize these results as follows:

Risky Play Conditionally on no breakdown having occurred, participants use the risky arm *more* in later periods.

4.5 History Dependence in Risky Play

To better understand the dynamics underlying risky play, we examine whether participants condition their choices on their own and their partner's previous experimentation within a game. We estimate linear probability models in which the dependent variable is an indicator equal to one if the participant chooses the risky arm in the current period. The sample consists of period-2 and period-3 choices in histories in which no breakdown had previously occurred. The main explanatory variables are the cumulative number of previous risky choices by the participant, the cumulative number of previous risky choices by the partner, an indicator for observable actions, and a period-3 indicator. Table II reports the results.

The results show that participants respond systematically to the history of play. Own previous experimentation is a strong predictor of current experimentation. More importantly for the strategic-learning mechanism, partner experimentation is also positively associated with current risky play. Thus, participants do not merely follow fixed individual propensities to experiment; their choices are also systematically related to histories generated by the other player's experimentation. The observable-action treatment effect remains positive after controlling for these history variables. At the same time, the period-3 coefficient is negative once prior experimentation is held fixed, consistent with the idea that raw period effects combine two opposing

Table II: History Dependence in Risky Play

	Dependent Variable: Current Risky Choice			
	(1) Baseline	(2) Interaction	(3) No-Breakdown	(4) Individual FE
Observable actions	0.066**	0.037	0.076**	
	(0.032)	(0.052)	(0.034)	
Own prior risky choices	0.256***	0.253***	0.265***	0.135***
	(0.048)	(0.048)	(0.050)	(0.047)
Partner prior risky choices	0.063***	0.049*	0.069**	0.069***
	(0.024)	(0.026)	(0.027)	(0.022)
Observable actions × partner prior risky choices		0.032		
		(0.039)		
Period 3	−0.245***	−0.246***	−0.251***	−0.163***
	(0.027)	(0.028)	(0.028)	(0.028)
Individual fixed effects	No	No	No	Yes
Observations	4,106	4,106	3,280	4,106
R^2	0.160	0.161	0.177	0.309

Notes: The table reports OLS linear probability models. The dependent variable is an indicator equal to one if the participant chooses the risky arm in the current period. Columns (1), (2), and (4) use period-2 and period-3 observations in histories in which no breakdown had previously occurred in the group. Column (3) restricts the sample to games in which no breakdown occurred during any of the three periods. Own prior risky choices and partner prior risky choices are cumulative counts of risky choices before the current period. The observable-actions indicator is absorbed by the individual fixed effects in Column (4). Standard errors, clustered at the matching-group level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

forces: successful experimentation makes the risky arm more attractive, whereas the shorter remaining horizon reduces the continuation value of experimentation.

The estimates also speak to whether participants respond similarly to their own and their partner's experimentation histories. The coefficient on own prior risky choices is larger than the coefficient on partner prior risky choices in all specifications. Wald tests reject equality in Columns (1)–(3) ($p = 0.004$, $p = 0.002$, and $p = 0.006$, respectively), though not in the individual fixed-effects specification ($p = 0.305$). Thus, while partner experimentation is positively associated with current risky play, participants' own experimentation histories appear to be the stronger predictor of subsequent behavior. This is natural in our setting. In the observable-actions treatment, participants observe both their own and their partner's previous actions and outcomes, so partner experimentation can directly affect subsequent choices. In the unobservable-actions treatment, by contrast, participants do not observe the partner's action unless a breakdown occurs. Hence, learning from others is necessarily more limited: participants can learn from their own experimentation and from observed breakdowns suffered by the partner, while the absence of a partner breakdown is a weaker signal because it does not reveal whether the partner actually experimented. Since we did not elicit beliefs, we interpret these results as revealed-choice evidence on how participants condition behavior on observed and inferable histories, rather than as direct evidence on belief updating.

To make the role of the opponent's action history more transparent, we also examine the direct relation between the opponent's period-1 action and period-2 risky play. We restrict attention to histories in which no breakdown occurred in period 1 and regress a participant's period-2 risky choice on the observable-actions treatment indicator, the participant's own period-1 action, and the opponent's period-1 action. Opponent risky play in period 1 is positively associated with the participant's period-2 risky choice: the coefficient is 0.114 (s.e. 0.036, $p = 0.002$). The corresponding coefficient on own period-1 risky play is larger, 0.265 (s.e. 0.069, $p < 0.001$). Descriptively, under observable actions, the probability of choosing risky in period 2 is 0.830 after an opponent chose risky in period 1, compared to 0.602 after an opponent chose safe. Thus, participants' period-2 choices respond systematically to the opponent's first-period action, especially when that action is observable.

Finally, we examine whether participants mimic the behavior of past partners across games. For each participant, we regress their first-period risky choice in game order o on their own first-period risky choice in game order $o-1$, the first-period risky choice of their previous partner in game order $o-1$, the observable-actions treatment indicator, and the order of the game. We find strong persistence in participants' own behavior: the coefficient on own previous first-period risky play is 0.303 ($p < 0.001$). By contrast, the coefficient on the previous partner's first-period risky choice is small and not statistically significant (0.042, $p = 0.179$). The observable-actions treatment effect remains positive (0.112, $p = 0.015$). We therefore find no robust evidence that participants mimic past partners across games; the treatment difference is not driven by cross-game imitation.

4.6 Heterogeneity in Experimentation Behavior

We also examine heterogeneity in experimentation behavior across participants. We classify participants according to their risky-choice frequency in pre-breakdown histories. Participants who choose the risky arm in at most one third of such histories are classified as persistent safe players; participants who choose the risky arm in at least two thirds of such histories are classified as persistent experimenters; the remaining participants are classified as intermediate experimenters.

Table III: Heterogeneity in Experimentation Behavior

	Observable Actions	Unobservable Actions	Difference
Panel A: Behavioral Types			
Persistent safe players	3.8%	21.2%	−17.3 pp
Intermediate experimenters	25.0%	36.5%	−11.5 pp
Persistent experimenters	71.2%	42.3%	28.8 pp
Panel B: Average Payoff by Type			
Persistent safe players	286	−177	463
Intermediate experimenters	2,356	764	1,592
Persistent experimenters	1,946	800	1,146

Notes: Participants are classified according to their risky-choice frequency in pre-breakdown histories. Persistent safe players choose the risky arm in at most one third of such histories; persistent experimenters choose the risky arm in at least two thirds of such histories; all remaining participants are classified as intermediate experimenters. Panel B reports average payoffs per game by behavioral type and treatment. The Difference column reports Observable Actions minus Unobservable Actions. The overall type distribution differs significantly across treatments ($p = 0.004$, chi-squared test). The treatment difference in the share of persistent experimenters is significant at $p = 0.005$, and the treatment difference in the share of persistent safe players is significant at $p = 0.015$ using Fisher exact tests.

Table III reports the distribution of behavioral types and their average payoffs by treatment. Observable actions substantially shift the distribution of types. With unobservable actions, 21.2% of participants are persistent safe players and 42.3% are persistent experimenters. With observable actions, only 3.8% are persistent safe players, while 71.2% are persistent experimenters. The overall type distribution differs significantly across treatments ($p = 0.004$, chi-squared test). The increase in the share of persistent experimenters is significant ($p = 0.005$, Fisher exact test), as is the decrease in the share of persistent safe players ($p = 0.015$, Fisher exact test).

Persistent safe players also earn the lowest average payoffs in both treatments. Thus, the aggregate treatment effect is reflected in a systematic shift away from persistent safe play and toward more frequent experimentation. This suggests that the higher experimentation intensity under observable actions is not driven by a small number of extreme participants, but instead corresponds to a broader shift in the distribution of experimentation behavior.

4.7 Econometric Robustness Tests

As a further robustness test, we estimate regressions that address three econometric concerns raised by the structure of the experiment: repeated observations at the participant level, dependence within matching groups, and possible order effects across the 25 games. Specifically, we estimate ordinary least-squares regressions with random effects at the participant and matching-group level and include a weighted learning function to control for potential learning or fatigue over the course of a session.[10] The random-effects specification captures unobserved heterogeneity across participants and matching groups, while clustering standard errors at the matching-group level accounts for dependence induced by repeated interaction and rematching within matching groups.

In particular, we regress experimentation intensity and individual payoffs on the treatment dummy *observable actions*, which is 0 for the unobservable-actions treatment and 1 for the observable-actions treatment. Recall that participants played the 25 games in random order and any order of these games that was used for participants in the observable actions sessions was replicated for participants in the unobservable-actions sessions. In order to verify that participants treated the games they successively played as independent games rather than as parts of a larger super-game, we define a weighted learning function $\{g_o\} = \{1/o\}$ where o ($o \in \{1, \cdots, 25\}$) corresponds to the random order in which each participant was exposed to each game. The function $\{g_o\}$ flexibly controls for non-linear trends in behavior across successive games, such as learning-by-doing or potential fatigue. All regressions control for trends over time using this weighted learning function. The results do not qualitatively change when we replace the learning function with a linear version such that $\{g_o\} = \{o\}$. Further, the results do not qualitatively change either when we include controls for matching groups or sessions, age, gender, field of study as well as attempts needed to correctly answer the quiz questions at the start of the experiment. To account for the fact that behavior within matching groups is not independent, we treat each matching group as the unit of statistical independence and cluster standard errors at the matching-group level. Our specification ensures that estimated treatment effects are not spuriously driven by time-dependent dynamics or unobserved fixed components, but instead identify the effect of action observability on experimentation intensity and payoffs. This also mitigates the concern that behavior might be driven by session-specific coordination on particular strategies. In a given session,

[10] Our results remain qualitatively unchanged in a fixed-effects specification.

separate matching groups were assigned to the bad-news observable-actions and bad-news unobservable-actions treatments. Clustering at the matching-group level therefore accounts for dependence within the relevant interaction group, and the results are robust to including session controls. The treatment effect remains positive and statistically significant.

Table IV lists the results from this analysis.

Table IV: Random-Effects Estimates of Experimentation Intensity and Payoffs

	Experimentation Intensity			Individual
	All	No Breakdown	Until Breakdown	Payoffs
Intercept	0.596***	0.586***	0.603***	418.199*
	(0.044)	(0.049)	(0.054)	(239.186)
Observable actions	0.157***	0.170***	0.280***	1398.080***
	(0.052)	(0.054)	(0.054)	(174.776)
Learning	0.034	0.040	−0.082	1059.966
	(0.026)	(0.029)	(0.106)	(1077.624)
σ_ϵ	0.287	0.268	0.293	8494.653
σ_u	0.216	0.212	0.243	0
Observations	2600	1248	336	2600
Between R^2	0.113	0.127	0.199	0.189

Notes: The table reports random-effects estimates. The dependent variable in Columns (1)–(3) is experimentation intensity; the dependent variable in Column (4) is individual payoffs. Observable actions is an indicator equal to one in the observable-actions treatment and zero in the unobservable-actions treatment. Learning is defined as $g_o = 1/o$, where o denotes the order in which the participant encountered the game. All regressions include random effects at the participant and matching-group level. Standard errors, clustered at the matching-group level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The coefficient on the learning variable is not statistically significant in any specification, and the estimated effect of observable actions remains positive and significant throughout. We therefore find no evidence that learning during the session drives our main results or that the main sample should be restricted to later games. We find a strong positive effect of observable actions on experimentation intensity across all games, games without breakdowns, games with breakdowns before the last period, and payoffs.

5 Concluding Remarks

This paper offers the first experimental investigation of *breakdown*-learning in a strategic setting. Observed behavior is consistent with strategic free-riding, thus documenting that free-riding on information because of strategic concerns also exists in bad-news learning environments, while differing in its form.

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Breakdowns in the Lab

Supplemental Appendix: Experimental Interface

The Environment with Observable Actions

June 3, 2026

Instructions

General Information

Welcome. This is an experiment in the economics of decision-making. If you pay close attention to these instructions, you can earn a significant amount of money.

Following these instructions, you will be asked to make decisions in a number of choice problems. You will be paid according to your choices, so read these instructions carefully and think before you decide.

Your computer screen will display useful information. Please ensure that this information remains private. If you have any questions, or need assistance of any kind, you can always raise your hand and one of the experimenters will help you privately.

One of the choice problems ("games") you will face has been randomly selected, and you will be paid according to your choices in that problem. Which problem was selected will be revealed at the end of the experiment. To maximize your earnings you can expect to receive, you should treat each choice problem ("game") as if it is the only one that determines your payment.

How Groups are Organized

This experiment consists of twenty-five games in total. At the beginning of each game, you are randomly matched to another participant in the room. Pairs of participants are randomly re-matched for each game; whether you have played with a particular participant in the past does not affect your probability of facing that same participant again in any future game.

How the Game Works

Every game consists of three rounds; you will make a decision in each round. That means that you have to decide whether you want to play the "safe" (SAFE) or the "risky" (RISKY) option in each round. Your previous choices in no way constrain your subsequent ones.

When you choose the SAFE option, you will receive no earnings in the current round.

If you choose the RISKY option, you will always earn **$2857**. In addition, you may, however, lose **$20000**. The chance of this happening depends on whether your risky option is good or bad. Whether it is good or bad is determined by the computer at the start of each game.
With a 67.6% chance, your <u>and the other participant's</u> risky option will be **bad**;
with a 32.4% chance, your <u>and the other participant's</u> risky option will be **good**.
Note that your, and the other participant's, risky option will always be of the **same** type (either both are good or both are bad).

If your RISKY option is **bad**, you may **lose $20000**. This will happen **with a 25% chance** in each round you use it. That is, with a 25% chance you lose $17143, and with a 75% chance you gain $2857. The probability that you incur this loss in a given round is constant over time, and does not depend on your previous earnings or choices, nor does it depend on the other participant's previous or current earnings or choices. It only depends on the type of the risky option (which is determined before the start of the game and which remains constant throughout the game) and your choice in the current round.

If your RISKY option is **good**, you will never incur a loss and will always **gain $2857** in each round you use it.

At the end of each round, you and the other participant observe each other's choices and earnings in that round. Note that by observing the behavior of their RISKY option (provided they use it) you can learn something about your own RISKY option as well.

Your earnings for the game are the sum of the earnings you will have accumulated over the three rounds of the game.

Please Note

The parameters are chosen in such a way that, *if you knew* the RISKY option to be good, you would be best off by always choosing it. Yet, *if you knew* the RISKY option to be bad, you would be best off by always choosing the SAFE option. The other participant is solving the exact same problem as you and has read the exact same instructions.

The Following Graphics Illustrate How the Game Evolves

Example Round 1 of 3

You are in Game **1** of **25**

You are randomly matched with **another** participant. You will stay in the same group for all 3 rounds.

Please make your choice by clicking on one of the two buttons.

SAFE RISKY

- In this example, you are in Round 1.
- You now need to choose between playing SAFE or RISKY.

Example Round 2 of 3

You are in Game **1** of **25**

EARNINGS

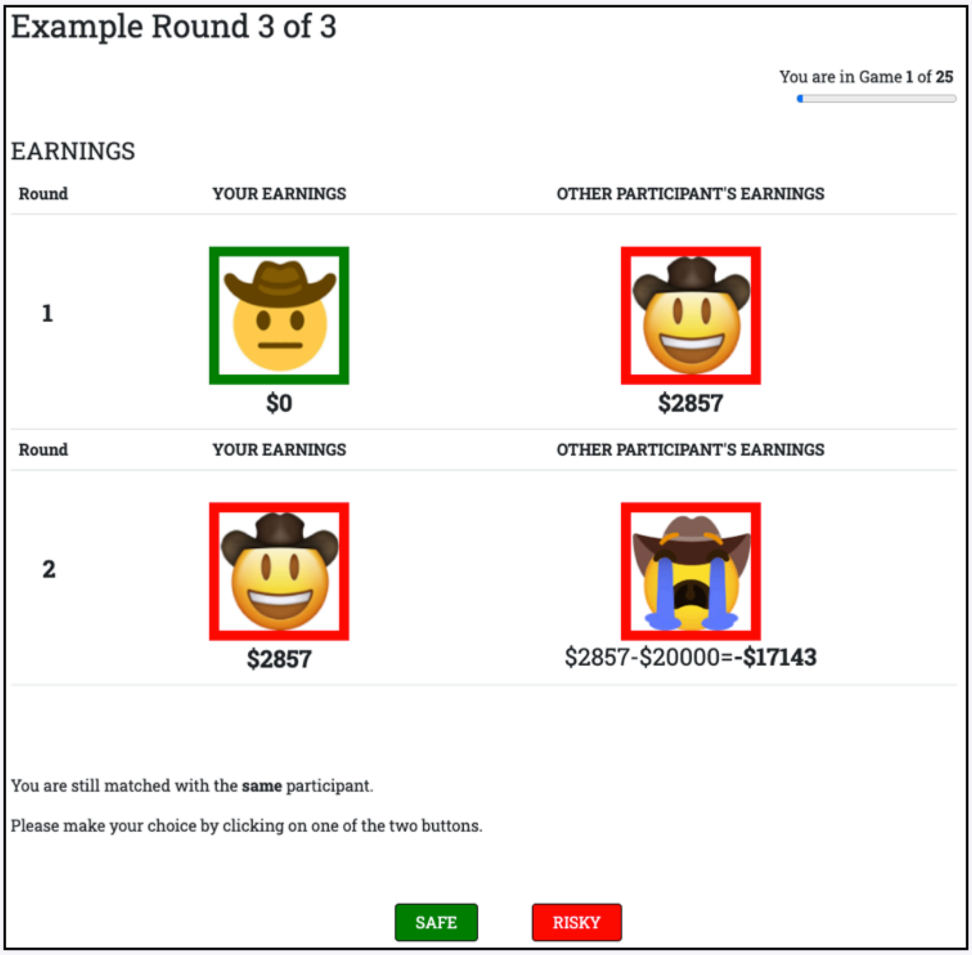
Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 $0	 $2857

You are still matched with the **same** participant.

Please make your choice by clicking on one of the two buttons.

SAFE RISKY

- In this example, you are in Round 2, and therefore you get to see your own and the other participant's choices and earnings in Round 1.
- The **left** column always shows **your** choices and earnings:
  - In this example, you have started playing safe (highlighted by the green frame), which does not yield a reward.
- The **right** column always shows the **other participant's** choices and earnings:
  - In this example, the other participant has played risky (highlighted by the red frame) in Round 1 and has not incurred a loss, thus earning $2857.
- Finally, you now need to choose between playing SAFE or RISKY.



- In this example, you are in Round 3, and therefore you get to see your own and the other participant's choices and earnings in Rounds 1 and 2.
- The **left** column always shows **your** choices and earnings:
    - In this example, you have played risky (highlighted by the red frame) in Round 2 and have not incurred a loss, thus earning $2857.
- The **right** column always shows the **other participant's** choices and earnings:
    - In this example, the other participant has played risky (highlighted by the red frame) in Round 2, yielding $2857, but has also incurred a loss of $20000:

      This means that **your and the other participant's** RISKY options are **bad**.
- Finally, you now need to choose between playing SAFE or RISKY.

Example Game Outcome

The game is over.

As a result, your earnings are **$2857.**

Round history

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	**$0**	**$2857**
Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
2	**$2857**	$2857-$20000=**-$17143**
Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
3	**$0**	**$0**

Next

- In this example, the game is over, and therefore you get to see your own and the other participant's choices and earnings in all rounds.
- The **left** column always shows **your** choices and earnings:
  - In this example, you have played safe (highlighted by the green frame) in Round 1, which does not yield a reward. In Round 2 you have played risky (highlighted by the red frame), which has yielded a reward of $2857; and in Round 3 you have played safe (highlighted by the green frame), which does not yield a reward. Thus, your earnings in this game are $2857.
- The **right** column always shows the **other participant's** choices and earnings:
  - In this example, the other participant has played risky (highlighted by the red frame) in Round 1, which has yielded a reward of $2857. In Round 2 they have played risky (highlighted by the red frame) and incurred a loss of $17143; and in Round 3 they have played safe (highlighted by the green frame), which does not yield a reward. Thus, the other participant's loss in this game is $14286.

Payment

In the experiment you will be making decisions that will earn you $ ("Dollars"). At the end of the experiment, the $ you have earned will be converted into Euros at an exchange rate of $ 10000 = € 1, and paid out in cash. This amount will be added to your participation payment of € 10.

Before the actual experiment starts, you will be asked to answer some questions. You must answer these correctly in order to proceed to the next question.

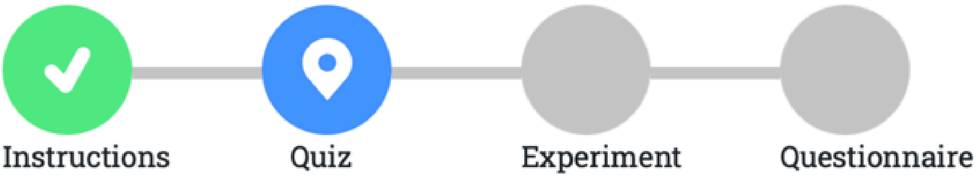
After completing the experiment, the computer will reveal which of the twenty-five games was randomly selected to determine your payment. You will be paid according to the choices you made in that particular game and you will be paid your earnings in cash. This protocol of determining payments suggests that you should choose in each game as if it is the only game that determines your payment.

Frequently Asked Question

Is this some kind of psychology experiment with an agenda you haven't told us? Answer. No. It is an economics experiment. If we do anything deceptive or don't pay you cash as described, then you can complain to the University of Vienna Research Ethics Board and we will be in serious trouble. These instructions are meant to clarify how you earn money, and our interest is in seeing how people make decisions.

Next

This button will be activated after 300 seconds. Please take your time to read through the instructions.



You have successfully finished reading the instructions.

The quiz, consisting of 13 questions in total, follows.

Next

Quiz Time!

Q1. The computer has randomly selected one of the games to determine your payment.

A Correct

B Incorrect

Quiz Time!

Q2. In each game (not round) you will be randomly matched with another participant in this session and stay together for that game.

A Correct

B Incorrect

Quiz Time!

Q3. In all games, the RISKY option is always **bad** and always leads to a loss of $20000 each time it is used.

A Correct

B Incorrect

Quiz Time!

Q4. If the RISKY option is **bad**, then it leads to a loss of $20000 with a chance of 25%.

A Correct

B Incorrect

Quiz Time!

Q5. If you knew the RISKY option to be **bad**, you would be best off by always choosing the SAFE option

A Correct

B Incorrect

Quiz Time!

Q6. If you experienced a loss of $20000 in an earlier round, you would be best off by always choosing the ____________ .

A SAFE option

B RISKY option

Quiz Time!

Q7. A **bad** RISKY option always leads to a loss of $20000 each time you use it.

A Correct

B Incorrect

Quiz Time!

Q8. A **good** RISKY option leads to a loss of $20000 with a 25% chance.

A Correct

B Incorrect

Quiz Time!

Q9. If the other participant has suffered a loss of $20000, this means that your RISKY option is **bad**.

A Correct

B Incorrect

Quiz Time!

Q10. If you have experienced a loss of $20000, this means that your RISKY option is **bad**.

A Correct

B Incorrect

Quiz Time!

Q11. If you choose the SAFE option in a given round, then you can never learn anything about your and the other participant's RISKY option in that round.

A Correct

B Incorrect

Quiz Time!

Q12. If both you and the other participant choose the SAFE option in a given round, then you cannot learn anything new about your and the other participant's RISKY option in that round.

A Correct

B Incorrect

Quiz Time!

Q13. The more you have observed you and/or the other participant using the RISKY option without experiencing a loss of $20000, the more inclined you should be to choose the RISKY option in the future.

A Correct

B Incorrect

Instructions Quiz Experiment Questionnaire

You have successfully finished the quiz.

The experiment follows. When you are ready please click "Next" to start the experiment.

Next

Round 1 of 3

You are in Game **1** of **25**

You are randomly matched with **another** participant. You will stay in the same group for all 3 rounds.

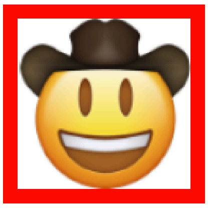
Please make your choice by clicking on one of the two buttons.

SAFE RISKY

Round 2 of 3

You are in Game **1** of **25**

EARNINGS

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **$2857**	 $2857-$20000=**-$17143**

You are still matched with the **same** participant.

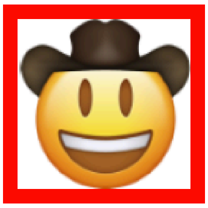
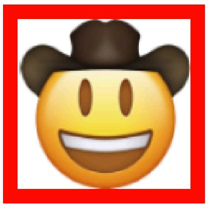
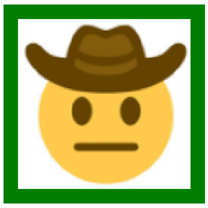
Please make your choice by clicking on one of the two buttons.

SAFE RISKY

Round 3 of 3

You are in Game **1** of **25**

EARNINGS

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **$2857**	 $2857-$20000=**-$17143**
Round	**YOUR EARNINGS**	**OTHER PARTICIPANT'S EARNINGS**
2	 **$2857**	 **$0**

You are still matched with the **same** participant.

Please make your choice by clicking on one of the two buttons.

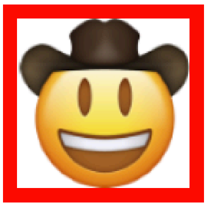
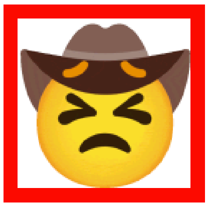
SAFE RISKY

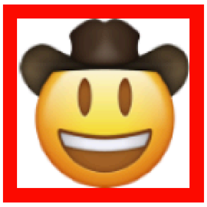
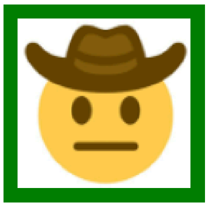
Game Outcome

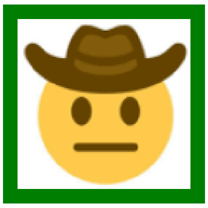
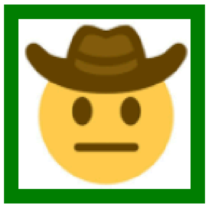
The game is over.

As a result, your earnings are **$5714**.

Round history

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **$2857**	 $2857-$20000=**-$17143**

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
2	 **$2857**	 **$0**

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
3	 **$0**	 **$0**

Next

Instructions Quiz Experiment Questionnaire

You have successfully finished the main part of the experiment.

A brief questionnaire follows.

Your answers will be kept confidential and will not affect your earnings for today's experiment.

Please state your age:

Please state your gender:

Please state your degree and field of study:

Please briefly explain, in your own words, the rules of today's experiment:

Please briefly describe how you reached your decisions in this experiment:

Please briefly describe how, in your opinion, other participants reached their decisions in this experiment:

Next

Thank you for participating in this experiment!

Your Earnings

The randomly selected game for payment is **Game #21**. Your total earnings are therefore **$5714**.

This corresponds to **€0.57**.

In total, you earned **€10.57** in this experiment. This includes your participation payment of €10 for taking part in this experiment.

Breakdowns in the Lab

Supplemental Appendix: Experimental Interface

The Environment with Unobservable Actions

June 3, 2026

Instructions

General Information

Welcome. This is an experiment in the economics of decision-making. If you pay close attention to these instructions, you can earn a significant amount of money.

Following these instructions, you will be asked to make decisions in a number of choice problems. You will be paid according to your choices, so read these instructions carefully and think before you decide.

Your computer screen will display useful information. Please ensure that this information remains private. If you have any questions, or need assistance of any kind, you can always raise your hand and one of the experimenters will help you privately.

One of the choice problems ("games") you will face has been randomly selected, and you will be paid according to your choices in that problem. Which problem was selected will be revealed at the end of the experiment. To maximize your earnings you can expect to receive, you should treat each choice problem ("game") as if it is the only one that determines your payment.

How Groups are Organized

This experiment consists of twenty-five games in total. At the beginning of each game, you are randomly matched to another participant in the room. Pairs of participants are randomly re-matched for each game; whether you have played with a particular participant in the past does not affect your probability of facing that same participant again in any future game.

How the Game Works

Every game consists of three rounds; you will make a decision in each round. That means that you have to decide whether you want to play the "safe" (SAFE) or the "risky" (RISKY) option in each round. Your previous choices in no way constrain your subsequent ones.

When you choose the SAFE option, you will receive no earnings in the current round.

If you choose the RISKY option, you will always earn **$2857**. In addition, you may, however, lose **$20000**. The chance of this happening depends on whether your risky option is good or bad. Whether it is good or bad is determined by the computer at the start of each game.
With a 67.6% chance, your <u>and the other participant's</u> risky option will be **bad**;
with a 32.4% chance, your <u>and the other participant's</u> risky option will be **good**.
Note that your, and the other participant's, risky option will always be of the **same** type (either both are good or both are bad).

If your RISKY option is **bad**, you may **lose $20000**. This will happen **with a 25% chance** in each round you use it. That is, with a 25% chance you lose $17143, and with a 75% chance you gain $2857. The probability that you incur this loss in a given round is constant over time, and does not depend on your previous earnings or choices, nor does it depend on the other participant's previous or current earnings or choices. It only depends on the type of the risky option (which is determined before the start of the game and which remains constant throughout the game) and your choice in the current round.

If your RISKY option is **good**, you will never incur a loss and will always **gain $2857** in each round you use it.

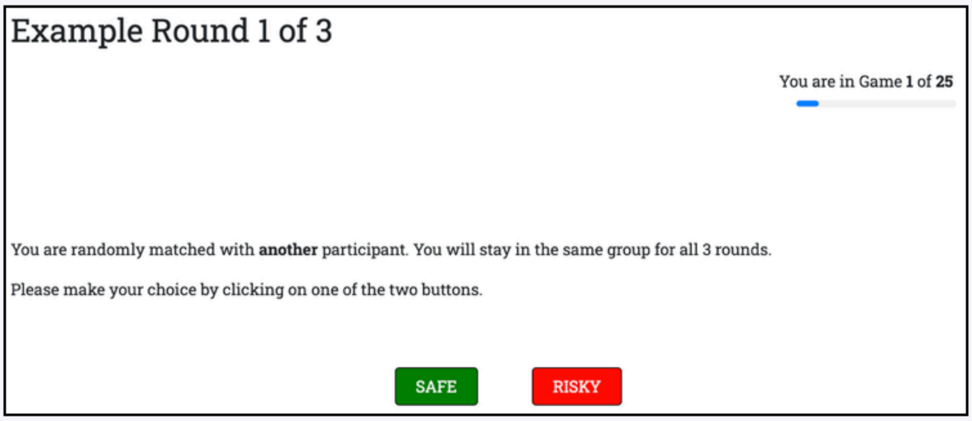
At the end of each round, you observe only if the other participant incurred a loss of **$20000** from their RISKY option as well as your own choice and earnings.

Your earnings for the game are the sum of the earnings you will have accumulated over the three rounds of the game.

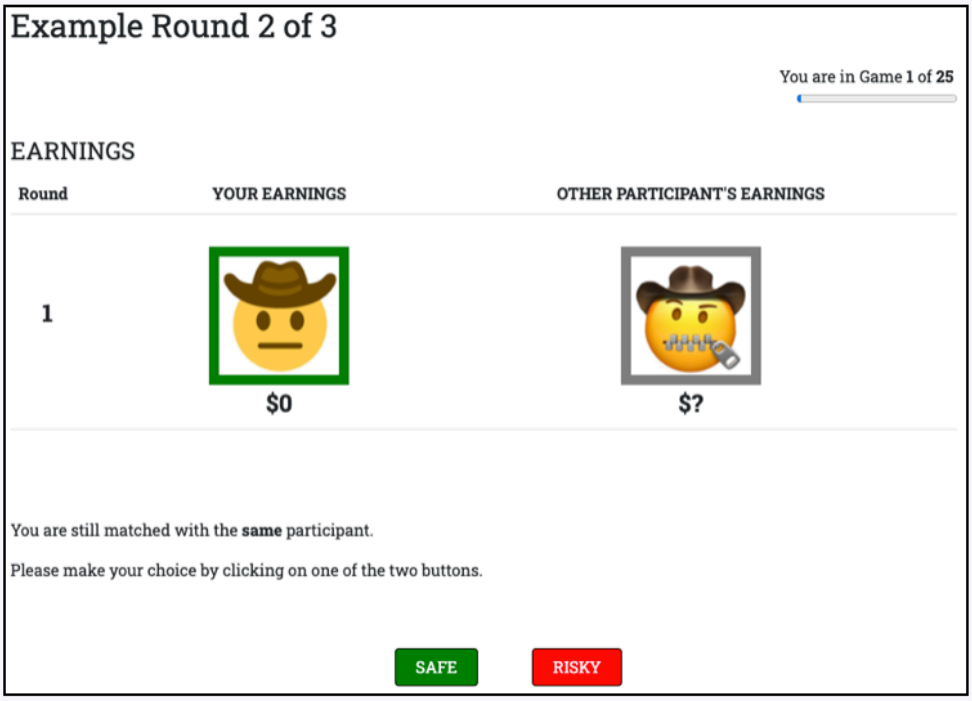
Please Note

The parameters are chosen in such a way that, *if you knew* the RISKY option to be good, you would be best off by always choosing it. Yet, *if you knew* the RISKY option to be bad, you would be best off by always choosing the SAFE option. The other participant is solving the exact same problem as you and has read the exact same instructions.

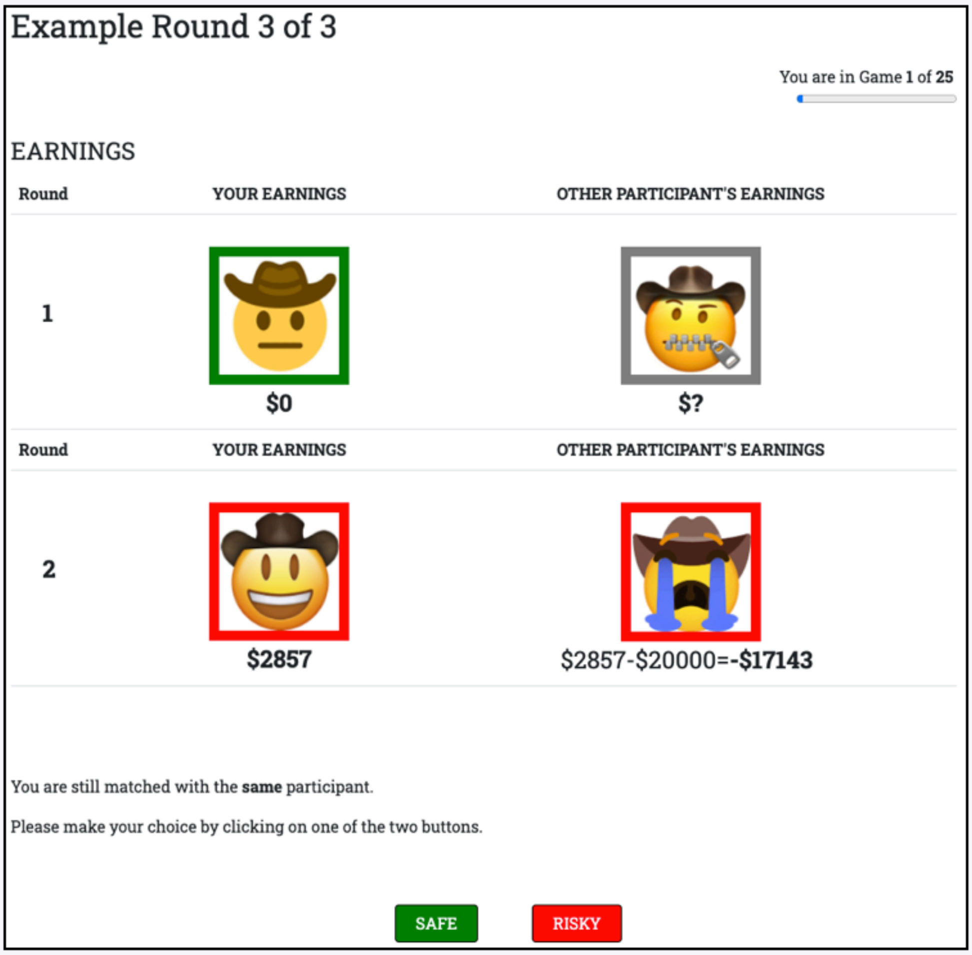
The Following Graphics Illustrate How the Game Evolves

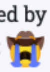


- In this example, you are in Round 1.
- You now need to choose between playing SAFE or RISKY.



- In this example, you are in Round 2, and therefore you get to see your own choices and earnings in Round 1 and whether or not the other participant has incurred a loss of $20000.
- The **left** column always shows **your** choices and earnings:
  - In this example, you have started playing safe (highlighted by the green frame), which does not yield a reward.
- The **right** column always shows whether or not the **other participant** has incurred a loss of $20000:
  - In this example, the other participant has played either safe or risky (highlighted by the grey frame) in Round 1 and has not incurred a loss. So, their earnings in Round 1 are either $0 if they chose the safe option or $2857 if they chose the risky option.
- Finally, you now need to choose between playing SAFE or RISKY.



- In this example, you are in Round 3, and therefore you get to see your own choices and earnings in Rounds 1 and 2, and whether or not the other participant has incurred a loss of $20000.
- The **left** column always shows **your** choices and earnings:
  - In this example, you have played risky (highlighted by the red frame) in Round 2 and have not incurred a loss, thus earning $2857.
- The **right** column always shows whether or not the **other participant** has incurred a loss of $20000:
  - In this example, the other participant has played risky (highlighted by the red frame) in Round 2, yielding $2857, but has also incurred a loss of $20000: 

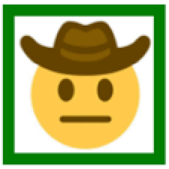
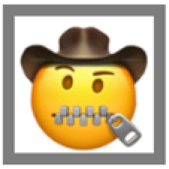
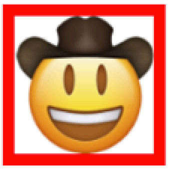
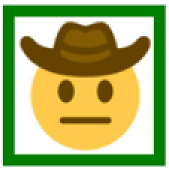
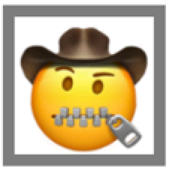
    This means that **your and the other participant's** RISKY options are **bad**.
- Finally, you now need to choose between playing SAFE or RISKY.

Example Game Outcome

The game is over.

As a result, your earnings are **$2857.**

Round history

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **\$0**	 **\$?**
Round	**YOUR EARNINGS**	**OTHER PARTICIPANT'S EARNINGS**
2	 **$2857**	 $2857-$20000=-**$17143**
Round	**YOUR EARNINGS**	**OTHER PARTICIPANT'S EARNINGS**
3	 **\$0**	 **\$?**

Next

- In this example, the game is over, and therefore you get to see your own choices and earnings in all rounds, and whether or not the other participant has incurred losses of $20000.
- The **left** column always shows **your** choices and earnings:
  - In this example, you have played safe (highlighted by the green frame) in Round 1, which does not yield a reward. In Round 2 you have played risky (highlighted by the red frame), which has yielded earnings of $2857; and in Round 3 you have played safe (highlighted by the green frame), yielding no reward. Thus, your earnings in this game are $2857.
- The **right** column always shows whether or not the **other participant** has incurred a loss of $20000:
  - In this example, the other participant has played either safe or risky (highlighted by the grey frame) in Round 1 with no loss but potentially with earnings of $2857; and risky in Round 2 and incurred a loss of $17143. In Round 3, they have played either safe or risky (highlighted by the grey frame) with no loss but potentially with earnings of $2857.

Payment

In the experiment you will be making decisions that will earn you $ ("Dollars"). At the end of the experiment, the $ you have earned will be converted into Euros at an exchange rate of $ 10000 = € 1, and paid out in cash. This amount will be added to your participation payment of € 10.

Before the actual experiment starts, you will be asked to answer some questions. You must answer these correctly in order to proceed to the next question.

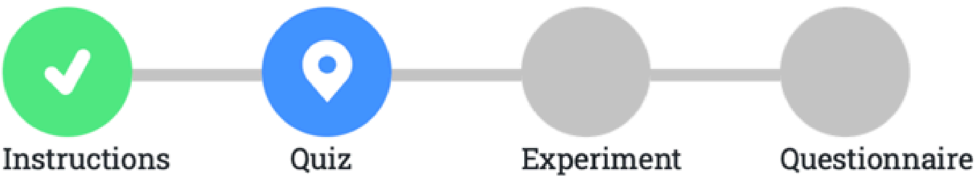
After completing the experiment, the computer will reveal which of the twenty-five games was randomly selected to determine your payment. You will be paid according to the choices you made in that particular game and you will be paid your earnings in cash. This protocol of determining payments suggests that you should choose in each game as if it is the only game that determines your payment.

Frequently Asked Question

Is this some kind of psychology experiment with an agenda you haven't told us? Answer. No. It is an economics experiment. If we do anything deceptive or don't pay you cash as described, then you can complain to the University of Vienna Research Ethics Board and we will be in serious trouble. These instructions are meant to clarify how you earn money, and our interest is in seeing how people make decisions.

Next

This button will be activated after 405 seconds. Please take your time to read through the instructions.



You have successfully finished reading the instructions.

The quiz, consisting of 13 questions in total, follows.

Next

Quiz Time!

Q1. The computer has randomly selected one of the games to determine your payment.

A Correct

B Incorrect

Quiz Time!

Q2. In each game (not round) you will be randomly matched with another participant in this session and stay together for that game.

A Correct

B Incorrect

Quiz Time!

Q3. In all games, the RISKY option is always **bad** and always leads to a loss of $20000 each time it is used.

A Correct

B Incorrect

Quiz Time!

Q4. If the RISKY option is **bad**, then it leads to a loss of $20000 with a chance of 25%.

A Correct

B Incorrect

Quiz Time!

Q5. If you knew the RISKY option to be **bad**, you would be best off by always choosing the SAFE option

A Correct

B Incorrect

Quiz Time!

Q6. If you experienced a loss of $20000 in an earlier round, you would be best off by always choosing the ____________ .

A SAFE option

B RISKY option

Quiz Time!

Q7. A **bad** RISKY option always leads to a loss of $20000 each time you use it.

A Correct

B Incorrect

Quiz Time!

Q8. A **good** RISKY option leads to a loss of $20000 with a 25% chance.

A Correct

B Incorrect

Quiz Time!

Q9. If the other participant has suffered a loss of $20000, this means that your RISKY option is **bad**.

A Correct

B Incorrect

Quiz Time!

Q10. If you have experienced a loss of $20000, this means that your RISKY option is **bad**.

A Correct

B Incorrect

Quiz Time!

Q11. If you choose the SAFE option in a given round, then you can never learn anything about your and the other participant's RISKY option in that round.

A Correct

B Incorrect

Quiz Time!

Q12. If you choose the SAFE option in a given round, then you cannot learn anything new about your and the other participant's RISKY option in that round unless the other participant experiences a loss of $20000 from choosing their RISKY option.

A Correct

B Incorrect

Quiz Time!

Q13. The more you have used the RISKY option without experiencing a loss of $20000, the more inclined you should be to choose the RISKY option in the future unless the other participant has experienced a loss of $20000 from choosing their RISKY option.

A Correct

B Incorrect

Instructions — Quiz — Experiment — Questionnaire

You have successfully finished the quiz.

The experiment follows. When you are ready please click "Next" to start the experiment.

Next

Round 1 of 3

You are in Game **1** of **25**

You are randomly matched with **another** participant. You will stay in the same group for all 3 rounds.

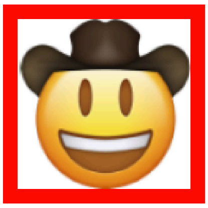
Please make your choice by clicking on one of the two buttons.

SAFE RISKY

Round 2 of 3

You are in Game **1** of **25**

EARNINGS

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **$2857**	 $2857-$20000=**-$17143**

You are still matched with the **same** participant.

Please make your choice by clicking on one of the two buttons.

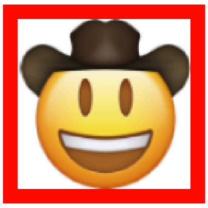
SAFE RISKY

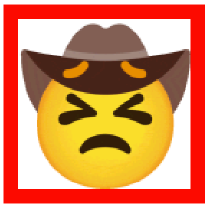
Round 3 of 3

You are in Game **1** of **25**

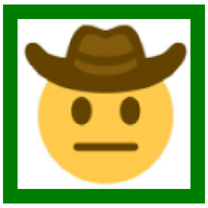
EARNINGS

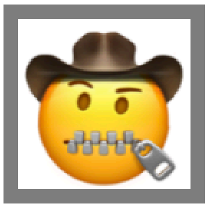
Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	**$2857**	$2857-$20000=**-$17143**





Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
2	**$0**	**$?**





You are still matched with the **same** participant.

Please make your choice by clicking on one of the two buttons.

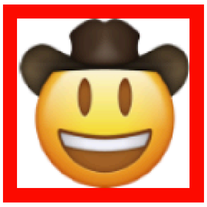
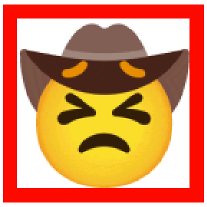
SAFE RISKY

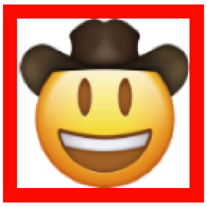
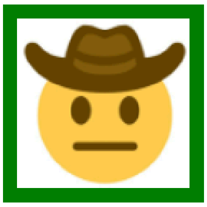
Game Outcome

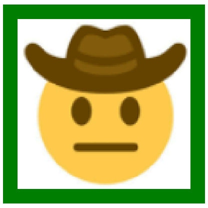
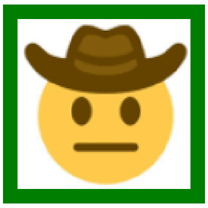
The game is over.

As a result, your earnings are **$5714**.

Round history

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
1	 **$2857**	 $2857-$20000=**-$17143**

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
2	 **$2857**	 **$0**

Round	YOUR EARNINGS	OTHER PARTICIPANT'S EARNINGS
3	 **$0**	 **$0**

Next

Thank you for participating in this experiment!

Your Earnings

The randomly selected game for payment is **Game #21**. Your total earnings are therefore **$2857**.

This corresponds to **€0.29**.

In total, you earned **€10.29** in this experiment. This includes your participation payment of €10 for taking part in this experiment.