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Author manuscript

*Science*. Author manuscript; available in PMC 2019 February 16.

Published in final edited form as:

*Science*. 2018 July 13; 361(6398): 178–181. doi:10.1126/science.aar8644.

## Sensitivity to “sunk costs” in mice, rats, and humans

Brian M. Sweis<sup>1,2</sup>, Samantha V. Abram<sup>3</sup>, Brandy J. Schmidt<sup>2</sup>, Kelsey D. Seeland<sup>2</sup>, Angus W. MacDonald III<sup>3</sup>, Mark J. Thomas<sup>2,3</sup>, and A. David Redish<sup>2,\*</sup>

<sup>1</sup>Graduate Program in Neuroscience and Medical Scientist Training Program, University of Minnesota, Minneapolis, MN 55455, USA.

<sup>2</sup>Department of Neuroscience, University of Minnesota, Minneapolis, MN 55455, USA.

<sup>3</sup>Department of Psychology, University of Minnesota, Minneapolis, MN 55455, USA.

### Abstract

Sunk costs are irrecoverable investments that should not influence decisions, because decisions should be made on the basis of expected future consequences. Both human and nonhuman animals can show sensitivity to sunk costs, but reports from across species are inconsistent. In a temporal context, a sensitivity to sunk costs arises when an individual resists ending an activity, even if it seems unproductive, because of the time already invested. In two parallel foraging tasks that we designed, we found that mice, rats, and humans show similar sensitivities to sunk costs in their decision-making. Unexpectedly, sensitivity to time invested accrued only after an initial decision had been made. These findings suggest that sensitivity to temporal sunk costs lies in a vulnerability distinct from deliberation processes and that this distinction is present across species.

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Traditional economic theory suggests that decisions should be based on valuations of future expectations that ignore spent resources that cannot be recovered [sunk costs (1)]. However, extensive evidence shows that humans factor such sunk costs into prospective decisions, even when faced with better alternatives (2, 3). Although early reports claimed that humans are uniquely sensitive to sunk costs (2, 3), it is becoming increasingly clear that nonhuman animals exhibit parallel behaviors (4).

Previous nonhuman animal studies that attempted to model the sunk cost phenomenon have yielded conflicting evidence (4, 5). Observational and experimental field studies in swallows, sparrows, mice, and bluegills have found evidence both for and against the sunk cost effect in behaviors relating to parental investment and willingness to care for young (6–10). Yet in such studies, it has been difficult to disentangle influences of investment history from those of future prospects. Laboratory operant conditioning paradigms in pigeons and rats that control for future expectations when looking at reinforcement learning behaviors

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\*Corresponding author. redish@umn.edu.

**Author contributions:** B.M.S., S.V.A., and B.J.S. and K.D.S. performed the experiments in mice, humans, and rats, respectively. B.M.S. analyzed the data and wrote the manuscript. A.D.R., M.J.T., and A.W.M. supervised the project and cowrote the manuscript.

**Competing interests:** The authors have no competing interests.

**Data and materials availability:** Data are included in supplementary materials

have demonstrated that nonhuman animals show increased work ethic or suboptimal perseverative reward-seeking behaviors that escalate with prior investment amount (11, 12). However, these observations often relied on situations of information uncertainty, where subjects overworked in the absence of progress-indicating cues. These observations also often relied on automation or habit-like behaviors (e.g., repetitive lever pressing) driving continued reward pursuit. Such confounding factors in nonhuman animal studies obscure translation to human sunk cost effects, which do not depend on these mechanisms.

Laboratory foraging tasks provide an alternative approach to study decision-making by using naturalistic behaviors that carry both ecological validity and evolutionary significance and are translatable across species (13). Foraging tasks rely on optimizing reward-seeking under conditions of limited resources, making them economic tasks.

We designed a foraging task in which subjects spent time from a limited time budget waiting for rewards [Fig. 1, Restaurant Row (14) and web-Surf (15)]. The division of time spent during the task reveals the economic preferences of the subjects. All three species learned to forage in a way that revealed preferences for certain rewards, and all species used reliable subjective valuation strategies to decide between multiple competing reward offers (supplementary text S1). Our neuro-economic tasks directly test sensitivity to sunk costs across species.

Flavors and genres of rewards (Fig. 1) allowed us to measure subjective preferences as a function of cost, avoiding the confounding possibility that different reward sizes might require different consumption times. Multiple zones allowed us to characterize multiple valuation processes involved in decisions: initial commitment valuations (offer zone), secondary reevaluations (wait zone), and postconsumption hedonic valuations (supplementary text S1 and S2). In this task, two key factors minimized information uncertainty and automated reward-seeking behavior as potential confounding factors: (i) Subjects were provided full information on cost and investment progress (tones counting down or download bar shrinking), and (ii) earning rewards required subjects to wait and withhold quitting after making an initial acceptance decision (rather than requiring a repetitive action).

To address susceptibility to sunk costs, we examined quit decisions in the wait zone. These behaviors involve the abandonment of continued reward pursuit despite having made prior investments (partial waiting) while on a limited budget (time). We parameterized the probability of earning a reward in the wait zone as a function of the remaining time investment required to earn a reward (future costs) and the prior time investment already spent waiting in the wait zone [past (sunk) costs; fig. S3]. The data yielded many samples across all conditions of time remaining and time spent (fig. S4), which allowed us to measure the extent to which irrecoverable prior investments (sunk costs) escalated wait zone commitment (fig. S5).

We found that mice, rats, and humans demonstrated robust sunk cost effects [analysis of variance (ANOVA) collapsing across all sunk cost conditions: mice,  $F=30.75$ ,  $P<0.0001$ ; rats,  $F=45.65$ ,  $P<0.0001$ ; humans,  $F=3.95$ ,  $P<0.0001$ ] (Fig. 2). Importantly, increasing

prior investment amounts generated a continuously stronger sunk cost effect (example post-hoc comparison between +1-s and +5-s sunk costs: mice,  $F=45.49$ ,  $P<0.0001$ ; rats,  $F=54.41$ ,  $P<0.0001$ ; humans,  $F=4.21$ ,  $P<0.05$ ) (Fig. 2)—a critical tenet of the sunk cost fallacy (2, 4).

Time spent in the offer zone also detracts from the total time budget, and a similar analysis can be performed (fig. S6). In contrast to our findings for reevaluation processes in the wait zone, we found no effect of time spent in the offer zone. That is, the amount of time spent in the offer zone did not alter the probability of earning rewards once in the wait zone (ANOVA collapsing across all offer conditions: mice,  $F=1.55$ ,  $P=0.23$ ; rats,  $F=0.77$ ,  $P=0.39$ ; humans:  $F=0.12$ ,  $P=0.74$ ) (Fig. 3). Importantly, the delay to reward did not start counting down while the subject remained in the offer zone. This meant that the animal was choosing between distant options and had not yet invested in the offer. This lack of an effect of time spent in the offer zone on progress abandonment once committed suggests that waste avoidance, overall resource depletion, and loss aversion are insufficient explanations of sunk cost-driven escalation of reward-seeking behavior (figs. S7 to S11, supplementary text S2 and S3, and table SI). This also suggests that the offer zone and wait zone may access separable valuation processes and reveals a previously unknown determinant of susceptibility to sunk costs rooted in dissociable decision-making algorithms that are conserved across species.

A sensitivity to sunk costs defies optimality considerations (fig. S12). So, why has this cognitive bias persisted across evolution (supplementary text S4)? Three plausible psychological mechanisms that support sunk cost biases include (i) that it may be more advantageous to calculate reward value through effort expended, (ii) state-dependent valuation learning (SDVL), and (iii) within-trial contrast (WTC) processes (12,16–20). We discuss each of these below.

Because predicting valuations that depend on future outcomes is complex and difficult, animals may have evolved processes in which valuation is measured from effort spent rather than calculated explicitly as an estimate from constructed imaginations of potential future outcomes. Past effort is easy to measure but has a limited (though nonzero) correlation with future value. In contrast, calculating value from expected future outcomes has its own estimation uncertainties. If the correlation between past efforts and future value provides better predictions than the uncertainties of future outcomes, then animals may have evolved processes that use past effort as a proxy to estimate future value (16, 19). This can explain our observation that the postconsumption evaluation increases proportionally to the time spent waiting for the reward in all three species (fig. S13 and supplementary text S5). The fact that susceptibility to sunk costs only accrued in the wait zone implies that valuations in the offer zone depend on different processes that do not include measures of effort spent, but that may be more related to direct estimates of future value.

The SDVL theory hypothesizes that energy spent working toward reward receipt moves the individual into a poorer energy state, enhancing the perceived value of the yet-to-be-obtained reward (19, 20). This continued work can thus escalate commitment of continued reward pursuit with growing sunk costs. Similarly, the WTC theory describes the sunk cost

phenomenon as an increasing contrast between the decision-maker's current physical state and the goal (21). SDVL and WTC propose that either physiological or psychological states could drive added value, leading to a susceptibility to sunk costs. However, we did not observe sunk costs accruing during the offer zone, even though time spent in the offer zone is equivalent in physical and cognitive demands to time spent in the wait zone. Simple explanations from the WTC and SDVL theories would predict sunk costs to accrue in the offer zone as well.

Past-effort heuristics, SDVL, and WTC can indeed be prominent drivers of the sunk cost effect in our data when sunk cost effects are present. Therefore, our work brings up an intriguing question: How do decision-making processes differ between the wait zone (susceptible to sunk costs) and the offer zone (not susceptible to sunk costs)?

One possibility is that decisions made in the offer zone and wait zone may rely on separate processes that calculate value in distinct ways through dissociable neural circuits (22–24). Recent findings from other foraging tasks suggest that choosing to remain committed to already accepted options accesses different valuation algorithms than deliberating between distant options (16, 25–27). We suggest that wait zone decisions are driven by distinct mechanisms that depend on recently accumulated states, whereas offer zone decisions are driven by deliberation mechanisms that simulate future outcomes constructed from a more extended knowledge base of past experiences. There is strong neural evidence across these species to suggest that competing simulated future alternatives are being represented, evaluated, and compared in deliberation algorithms, whereas other decision-making systems depend on more immediate sensory signals that likely include interoceptive signals of effort expended and representations of internal state (23–24, 28–31) (fig. S8 and supplementary text S3). Each of these decision-making systems provides computational advantages better suited for different situations. Thus, these multiple valuation algorithms can each confer independent evolutionary advantages and can coexist and persist across time and species (22–24).

The sunk cost fallacy, by definition, arises from valuing spent resources that cannot be recovered. Our data finds that these sunk costs only accrue under specific situations in mice, rats, and humans. We suggest that multiple, parallel decision-making valuation algorithms implemented in dissociable neural circuits have persisted across species and over time through evolution. Our data imply that these different valuation algorithms are differentially susceptible to sunk costs. Past studies that reported conflicting findings across species may have failed to consider how different decision systems drive behavior (fig. S14 and supplementary text S6 and S7). Studies identifying differences in sensitivity to sunk costs should consider which decision-making processes are being accessed by the individual in a given task. Because these processes could change between species, or within species but across aging, stages of development, or circumstances, so too could sensitivity to sunk costs.

Using a translational approach in mice, rats, and humans, we find direct evidence in parallel tasks that the sunk cost phenomenon is conserved across species. Our findings highlight the utility of economic paradigms that can dissociate decision-making computations, using naturalistic tasks that are translatable across various species and that can be expanded to

survey individuals of varying ages or psychiatric populations. These tasks and findings may aid future research in education or neuropsychiatry by shedding light on diagnostic or intervention strategies and revealing the roles of neurally distinct decision systems.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## ACKNOWLEDGMENTS

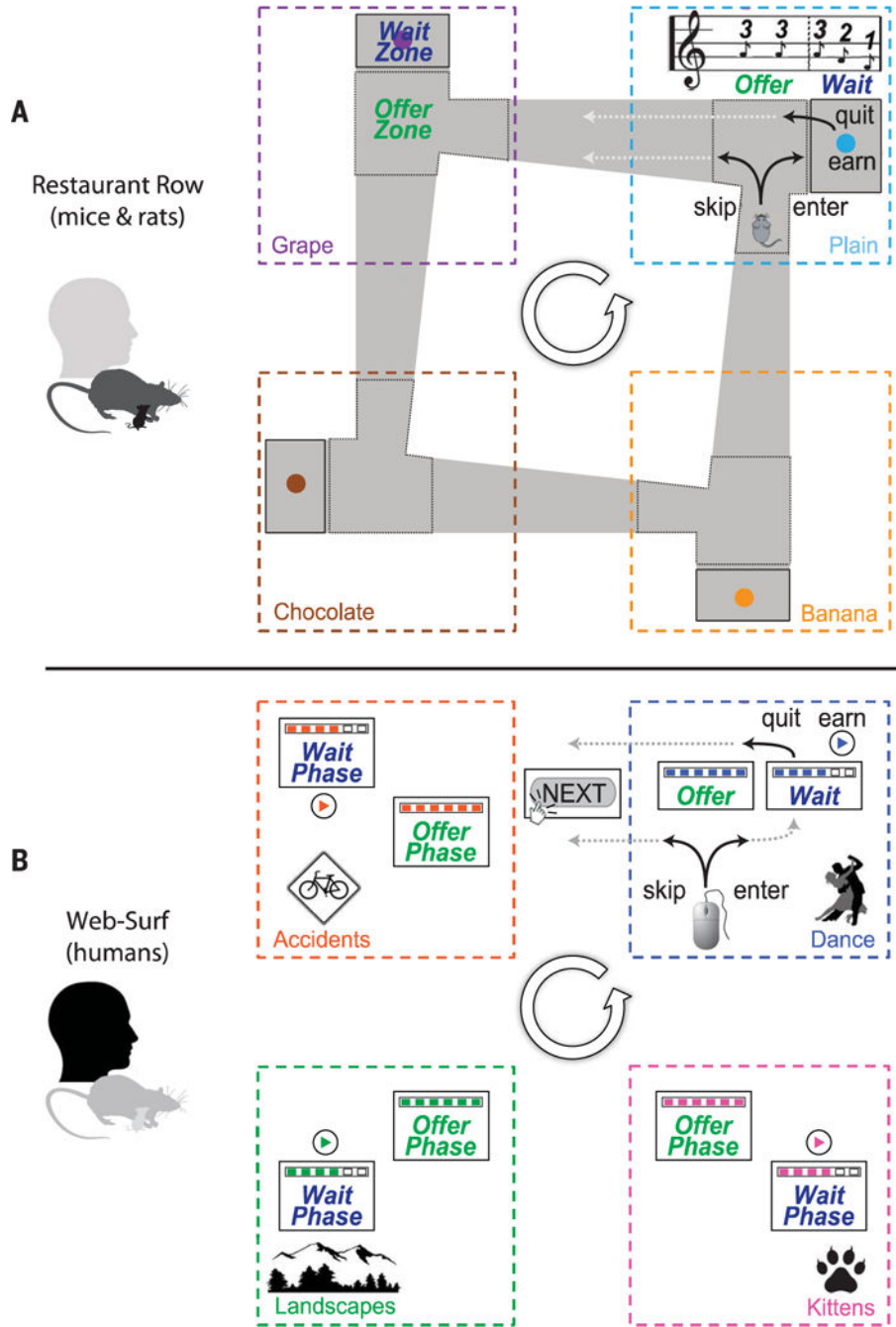
We thank the Redish, Thomas, and MacDonald laboratories for assistance.

**Funding:** R01DA019666 (M.J.T.), R01DA030672 (A.D.R.), R01 MH080318 (A.D.R.), R01 DA041808 (M.J.T.), R01 MH084861 (A.W.M.), MnDRIVE Neuromodulation Research Fellowships (B.M.S.), the Breyer-Longden Family Research Foundation (M.J.T.), MSTP NIGMS 5T32GM008244–25 (B.M.S.), GPN NIGMS 5T32GM008471–22 (B.M.S.), K02 DA035459 (M.J.T.), F30 DA043326 NRSA (B.M.S.), F31 DA040335 NRSA (S.VA), and F32 DA038392 NRSA (B.J.S.).

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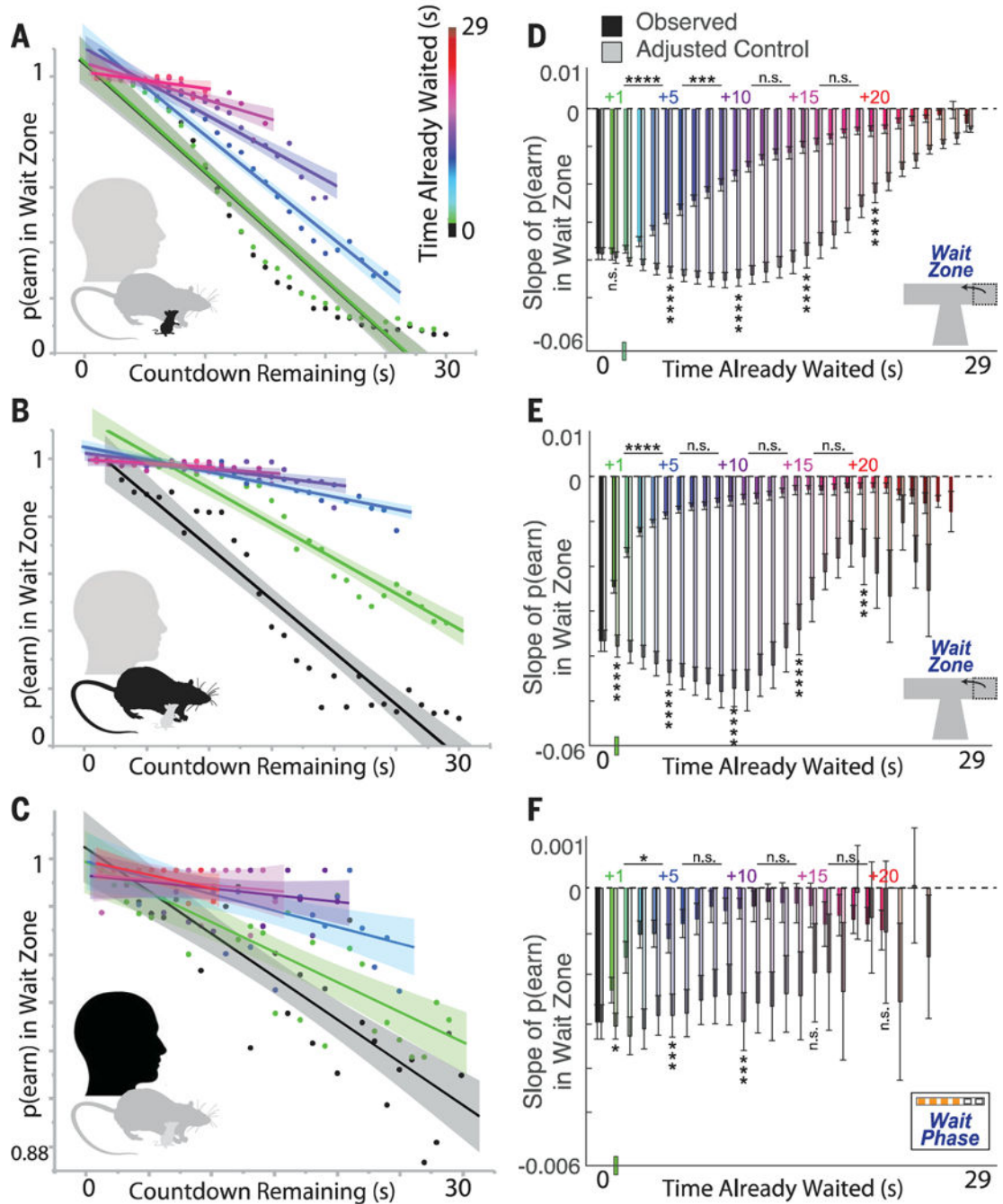


**Fig. 1. Task schematics.**

(A) In the Restaurant Row task, food-restricted rodents were trained on a maze in which they encountered serial offers for flavored rewards in four “restaurants.” Each restaurant contained a separate offer zone and wait zone. Tones sounded in the offer zone; a fixed tone pitch indicated the delay for which rodents would have to wait in the wait zone (1 to 30 s. random on offer entry). Tone pitch descended in the wait zone during the delay “countdown.” Rodents could quit the wait zone for the next restaurant during the countdown, terminating the trial. (B) In the web Surf task, humans performed an analogous

30-min computer-based foraging paradigm in which they encountered serial offers for short entertaining videos from four “galleries.” A static “download bar” appeared in the offer phase indicating delay length (1 to 30 s. random on offer entry), which did not begin downloading until after entering the wait phase. Downloads could be quit during the wait phase. Humans were also asked to rate each video on a scale from 1 (least enjoyable) to 4 (most enjoyable) after viewing and to rank the genres at the end of the session.

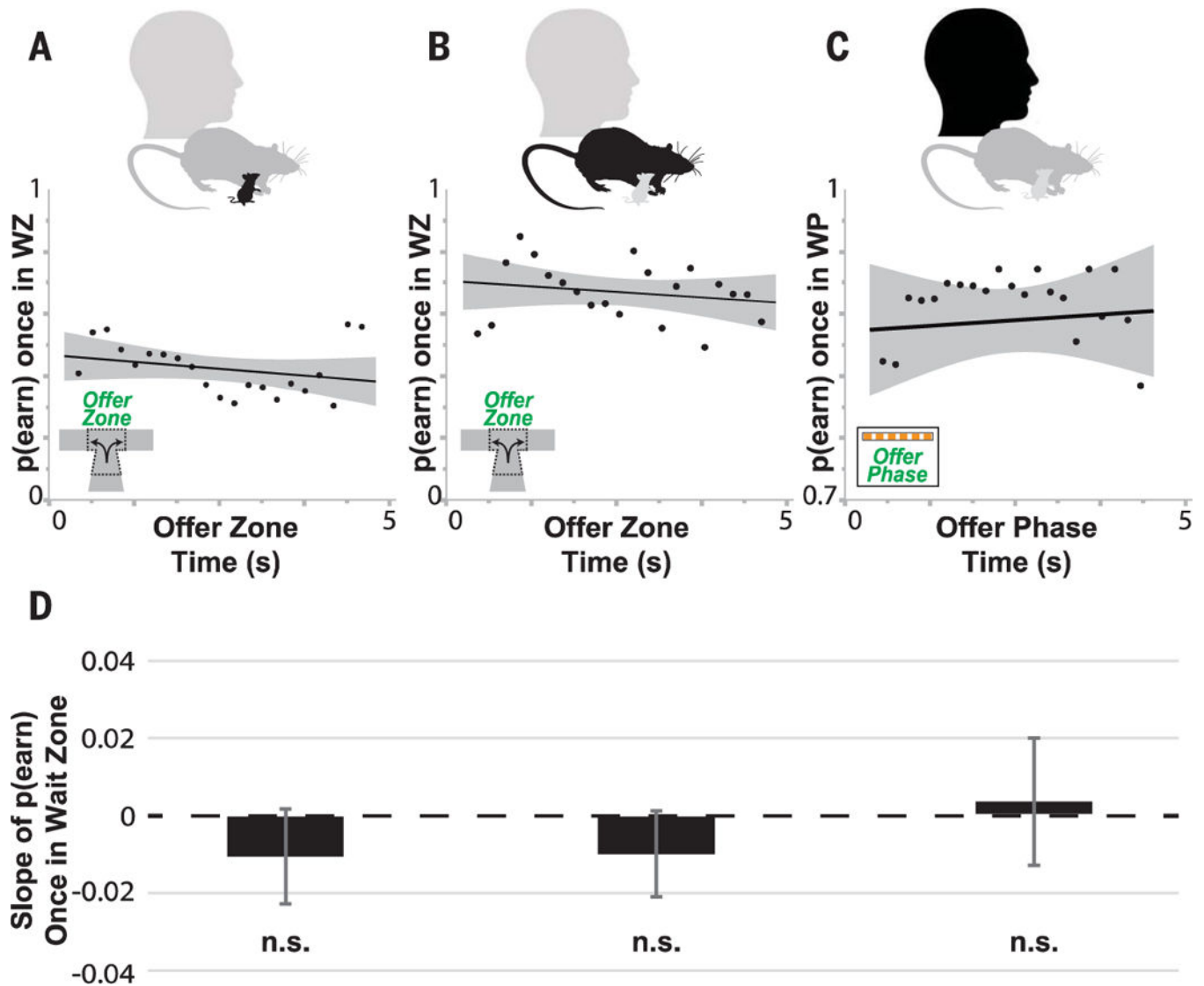




**Fig. 2. The amount of time spent waiting increases commitment to continuing reward pursuit in mice, rats, and humans.**

(A to C) Probability of earning a reward in the wait zone as a function of countdown time remaining in (A) mice, (B) rats, and (C) humans. Black data points indicate trials in which subjects had just entered the wait zone. Colored data points indicate time remaining in the countdown after subjects had already waited varying times (fig. S3). Linear regressions are plotted with 95% confidence interval shadings. (D to F) Slopes calculated from each linear regression in (A) to (C) (“observed”) and slopes recalculated iteratively from black data

points to match colored data ranges in (A) to (C) (“adjusted controls”) (fig. S5) are plotted  $\pm 1$  SEM. The colored tick on the x axis indicates time in the wait zone until the first significant sunk cost effect was observed. ANOVAs were used to compare slopes of linear regression models, testing for interactions with sunk cost conditions and controls, correcting for multiple comparisons. Not significant (n.s.),  $P > 0.05$ ; \* $P < 0.05$ ; \*\* $P < 0.01$ ; \*\*\* $P < 0.001$ ; \*\*\*\* $P < 0.0001$ .



**Fig. 3. Resources spent while deliberating do not contribute to the sunk cost effect.**

(A to C) Amount of time spent in the offer zone choosing to skip versus to enter did not influence the probability of earning versus quitting once in the wait zone after subjects chose to enter (fig. S6). Linear regressions are plotted with 95% confidence interval shadings. (D) Slopes calculated from linear regressions are plotted  $\pm 1$  SEM and are not significantly different from each other or zero in mice ( $F = 1.545$ ,  $P = 0.229$ ), rats ( $F = 0.767$ ,  $P = 0.392$ ), or humans ( $F = 0.117$ ,  $P = 0.737$ ), on the basis of an ANOVA with post-hoc comparisons against zero. n.s.,  $P > 0.05$ .