Learning and the Economics of Small Decisions

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Introduction

Mainstream analysis of economic behavior assumes that economic incentives can shape behavior even when individual agents have limited understanding of the environment (see related arguments in Nash[2], 1950; Smith[3], 1962). The shaping process in these cases is indirect: The economic incentives determine the agents' experience, and this experience in turn drives future behavior. Consider, for example, an agent that has to decide whether to cross the road at a particular location and time. The agent (say a chicken) is not likely to understand the exact incentive structure and compute the implied equilibria. Rather, the agent is likely to rely on experience with similar situations. The economic environment shapes this decision because it determines the relevant experience.

The current chapter reviews experimental studies that examine this shaping process. In order to clarify the relationship of the research reviewed here to classical research in behavioral and experimental economics it is constructive to consider the distinction

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[2] "It is unnecessary to assume that the participants have full knowledge of the total structure of the game, or the ability and inclination to go through any complex reasoning process" (Nash, 1950, p. 21)

[3] Smith showed that competitive equilibrium could be attained with small numbers of buyers and sellers with no knowledge of others' costs or values.

between "decisions from description" and "decisions from experience" (Hertwig et al., 2004) exemplified in Figure 1. Classical studies in behavioral economics tend to focus on decisions from description: They examine how people decide when they can rely on a complete description of the incentive structure. In contrast, the research reviewed here focuses on decisions from experience. In a pure decision from experience task (like the one demonstrated in Figure 1) the decision makers do not receive a prior description of the incentive structure. Rather, they have to rely on past experience, and gain relevant experience in the course of the experiment.

<Insert Figure 1>

The two lines of decision research have similar goals, but take very different routes towards achieving these goals. As a result, the two routes often identify and focus on different behavioral regularities. The main difference between the two routes is reflected by the relationship of the two lines of research to rational economic theory. The classical studies of decisions from description were designed to test the rationality assumption. The most influential papers in that research stream (e.g., Allais, 1953; Kahneman & Tversky, 1979; Fehr and Schmidt, 1999; Bolton & Ockenfels, 2000) present interesting deviations from rational choice, and elegant refinements of the rational models that capture these deviations. Gigernzer and Selten (2001) broadly refer to this line of research as the "subjective expected utility correction project." In contrast, the studies of decisions from experience focus on situations for which rational decision theory does not have clear predictions. When decisions makers rely on past experience, almost any behavior could be justified as rational given certain prior beliefs. Thus, the study of decisions from experience is not designed to test or refine rational decisions theory; it is rather intended to expand the set of situations that can be addressed with economic models that provide clear and useful predictions.

The significance of the difference between the behavioral regularities discovered in the two line of decision research is demonstrated by the effect of rare (low probability) events. Experimental studies reveal that people exhibit oversensitivity to rare events in decisions from description (Kahnemna & Tversky, 1979), and the opposite bias when they rely on experience (see Barron & Erev, 2003, and Section 1.1.3 below). This "experience-description gap" suggests that the common efforts to use models that were calibrated to capture decisions from description in order to address decisions from experience can lead to mismatched conclusions.

Many natural decision problems fall in-between decisions from description, and decisions from experience. For example, in 2003 when the USA President George W. Bush had to decide whether or not to engage militarily in Iraq he could rely on a description of the incentive structure, prepared by his consultants, but he could also rely on historical experiences in similar situations. And it is possible that these experiences could suggest that the description can be biased.

The importance of past experience is particularly clear in the context of small decisions. Small decision problems are defined here as situations in which the performance of a task requires decisions, and the expected consequence of each decision is relatively small. Many natural activities involve small decisions. For example, the road crossing task, described earlier, implies several small decisions. The agent can choose whether to start crossing in several points in time, and can then choose to change his or her mind.

We believe that small decisions can be of large economics importance. In many cases, small decisions can be highly consequential in the aggregate, and they can also be consequential in some rare specific cases. For example, small driving-related decisions lead to traffic jams, costly accidents, injuries and even fatalities. Moreover, in many cases small decisions shape subsequent big decisions. For instance, the small decisions between "doing homework" or "watching TV" as a kid, can affect the available alternatives in the big decisions among different career paths. Similarly, the big decision between different investment portfolios is only made if the agent has made the small decision to spend time (at a particular point in time) on evaluating her investments.[4]

[4] Another reason for our interest in small decisions is the feeling that external validity of laboratory research is larger in the context of small decisions that are similar to the laboratory tasks in many ways (e.g., low stakes, limited decision time), than in the context of large decisions. So, we have more to say about small decisions.

Economics, psychology, and the clicking paradigm. Most of the studies of learning and decisions from experience were conducted by psychologists, and were not designed to evaluate of the effect of the quantitative features of the incentive structure; they typically used non-monetary reinforcements like food, electric shocks, unpleasant noises, and verbal recognition. In order to clarify the economic implications of these studies we try to replicate the main results using the clicking paradigm presented in Figure 1. As demonstrated in Figure 1, the clicking paradigm focuses on the effect of experiencing monetary payoffs. The subjects do not receive prior description of the incentive structure, and have to base their decisions on the feedback (observed monetary outcomes) of previous decisions. To facilitate evaluation of the effect of this experience, each experiment includes many trials.

In order to illustrate the relationship of the current replications to the original demonstrations of the classical phenomena, we start the discussion of the key phenomena with a description of the original studies. Yet, we pay agreater attention to the clicking experiments.

Another advantage of the clicking replications involves the standardization of the experimental conditions (Hertwig & Ortmann, 2002). For example, it allows the use of the same instructions, same experimental design, and same subject population in all the replications. Since we focus on phenomena that were already documented in a wide set of conditions with wide set of subject populations (including very different animals), the focused standardization should not impair external validity.[5] The standardization is expected to clarify the role of the key factor: the effect of experiencing the incentive structure, and facilitate the development of models that capture this effect.

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[5] Erev and Livene-Tarandach (2005) showed that the attractive features of standard experimental paradigms could be used to reduce one of the differences between the natural and the social sciences. The difference they considered involves the frequency of exam questions that require predictions of the outcome of a particular experiment. Many of the questions in the natural sciences (about 64% in the sample of a physics GRE exams, used to evaluate applicants to graduate school), and very few questions in the social sciences (about 10% of the questions in Psychology GRE exam) require predictions. The focus on standard experimental paradigms can be used to reduce this gap by facilitating the development of short and clear prediction questions in the social sciences.

Three cognitive factors and the organization of the current review. Decisions from experience are likely to be affected by three classes of cognitive factors (see Erev & Roth, 1999). The first factor involves the "*cognitive strategies*" considered by the agents; that is, the strategies from which the agents learn. The cognitive strategies includes the possible actions (stage game strategies, "Select the left Key" or "Select the right key" in the basic clicking paradigm), but can also include other strategies like "Try to reciprocate" (see Section 3.3) or "Select best reply to the instructions" (see Section 1.9). The second factor involves the "*exploration policy*". That is, the tradeoff between collecting information and using the available information in order to get the best outcomes (see March, 1991). The third factor is the "*choice rule*:" the evaluation of past experiences that determines which strategy is preferred.

We believe that all three factors are important, but we also think that better understanding of the choice rule is likely to be most useful. Our belief is based on the observation that the "cognitive strategies" and the "exploration policy" tend to be situation specific. Small changes in the environment can change the strategies available and considered by the agents, and can change the value of exploration. In contrast, it is possible that the choice rule reflects a more robust cognitive process that is stable over situations and maybe also over species.

This belief led us start the current review with a focus on phenomena that can be replicated even when the effect of the first two factors is minimized. Specifically, we start with a focus on situations in which (1) it is reasonable to assume that the strategies considered by the agents can be approximated by the possible actions, and (2) exploration does not add information. The most important part of the current review is Section 1.1 that presents six robust behavioral phenomena that emerge in this setting, and a simple model that summarizes them. We consider situations in which exploration is important in Section 1.2, and delay the discussion of situations in which more sophisticated strategies are likely to be important to Sections 2 and 3.

Section 2 examines learning among of large number of alternatives, and learning in dynamic environments. The results highlight interactions between the basic properties of learning, summarized in Section 1, and other factors that can be abstracted as "cognitive strategies" that are implied by the task.

Section 3 reviews studies that examine the effect of social interactions on learning. The first part of this section highlights the generality of basic properties of learning reviewed in first sections. There are many situations in which social behavior can be accurately predicted based on simple models that were designed to capture behavior in individual choice tasks. Yet, there are also interesting exceptions to this generality. The main exceptions can be summarized with the assertion that in certain settings prior information changes the strategies that are considered in the learning process.

The chapter concludes with a discussion of the practical implications of experimental learning research. The discussion focuses on the economics of small decisions.

1. The basic properties of decisions from experience

The current section reviews the learning phenomena that we consider to be "most basic." They are most basic in the sense that they can be reliably replicated in the most basic versions of the clicking paradigm. We try to summarize the experimental result with the set of "sufficient regularities." That is, we hope that models that best capture these regularities will provide useful ex-ante predictions of behavior in any set of problems drawn from the population of decision problems considered here. Section 1.1 presents the regularities that can be replicated when the role of exploration is minimized, and Section 1.2 examines the effect of an increase in the value of exploration. Section 1.3 presents two choice prediction competitions that compare alternative models, and explore their predictive value.

1.1 Six basic regularities, and a model

Recall that the current review is based on the distinction between three cognitive factors that drive decisions from experience: The cognitive strategies, the exploration policy, and the choice rule. The present sub-section tries to clarify the basic properties of the choice rule. In order to achieve this goal it focuses on phenomena that can be replicated even when the role of sophisticated cognitive strategies and of the exploration policy is minimized. This "minimization" is achieved by using the 2-alternative clicking paradigm with complete feedback (cf. Figure 1), and a static payoff rule. After each choice in the clicking experiments, considered here, the agents receive feedback concerning their obtained payoff (the payoff from the key they selected), and the forgone payoff (the payoff that she could obtained had they selected the second key). The payoff of each key is drawn from a payoff distribution associated with that key. For example, if the key is associated with payoff distribution "11 with probability .5, -9 otherwise," it payoff will be 11 in 50% of the trials, and -9 in the other 50%. The fact that payoff rule is static implies that the distributions do not change during the experiment.

Our review revealed six robust behavioral regularities that emerge in this setting, and can be summarized by a simple reinforcement learning model. The model, initially proposed in Nevo and Erev (2012), is referred to as "Inertia, Sampling and Weighting" (I-SAW). In order to clarify the relationship between six basic phenomena and their abstraction in I-SAW we conclude the description of each class of experimental results with the "I-SAW explanation" of the main results. The model is presented in Section 1.1.7.

1.1.1 The Law of Effect.

Thorndike (1898) studied how cats learn to escape from puzzle boxes. The experiments included several trials: Each trial started with a placement of a cat in a puzzle box and ended when the cat exited the box. Evaluation of the learning curves (time to escape as a function of trial number) led Thorndike to conclude that the learning was gradual and stochastic. There was no evidence for sudden jumps in performance. Thorndike summarized this observation with the law of effect: *Choices that have led to good outcomes in the past are more likely to be repeated in the future*.

Studies that use the clicking paradigm reveal a similar pattern. Subjects tend to select the alternative that led to good outcome in the past, and the learning curves appear to reflect a gradual and stochastic process. Figure 2 demonstrates this pattern. Each curve in this figure summarizes the behavior of one participant in the first 25 trials of a simple experiment. The experiment involved a trivial choice task: One option, referred to as 'H' (High payoff) always provided a payoff of 1 Shekel, and the second option always led to a payoff of 0. The experiment used the basic clicking paradigm. That is, the participants did not receive prior information concerning the payoff rule, and could rely on feedback concerning the obtained and forgone payoffs. The results, presented in five blocks of five trials each, reveal that by the last block all three subjects learned to prefer the better option (H). Yet, the learning process is noisy. For example, the proportion of optimal choices of the “circle” subject go up to 100% by the second block, then go down to 60% in the third block, and then go up to 100% in the fifth block.

<Insert Figure 2>

I-SAW explanation: exploration mode: Recall that the current analysis focuses on conditions that minimize the value of exploration; the agents' actions had no effect on the collected information. However, the subjects were not informed that this is the case, and the observed behavior appears to reflect an attempt to explore the environment. Specifically, the observed deviations from "best reply to past experiences," can be an indication of an exploration the effect of selecting the "0" key. It seems that the subjects explore this effect even after observing that until the current trial it has always led to lower payoff than the other option. I-SAW captures this observation with the assertion that in certain trials the subjects choose an exploration mode.

1.1.2 The payoff variability effect

Myers and Sadler (1960) studied decisions from experience using a "card flipping" paradigm. In each trial of their studies, the participant saw one side of a card and had to decide whether to accept the payoff written on that side (the safe alternative), or the payoff written on the unobserved side of the card (the riskier option). Participants received feedback concerning their payoffs after each choice (the card was flipped only if the participant chose the riskier option). The results revealed that an increase in the payoff variability of the risky option (the variability of the payoff distribution on the unobserved side) reduced the proportion of choices that maximized expected payoff. Busemeyer and Townsend (1993) termed this pattern the "payoff variability effect" and highlighted its robustness.

We replicated this pattern in the clicking paradigm with the study of Problems 1, 2 and 3 (the H-rate in the brackets on the right are the proportion of H choices over all trials, EV is the expected value of the gamble):

Problem 1: (r=200, n=20, FB=complete, payoff in shekels in a randomly selected trial)

H	1 with certainty	[H-rate: 96%]
L	0 with certainty	

Problem 2 (same procedure as in Problem 1)

H	+11 with probability 0.5 -9 otherwise (EV = 1)	[H-rate: 58%]
L	0 points with certainty	

Problem 3 (same procedure as in Problem 1)

H	0 with certainty	[H-rate: 53%]
L	9 with probability 0.5 -11 otherwise (EV = -1)	

Problems 1, 2 and 3 were run in the same experiment in a within-participant design. Each of 20 participants (n=20) faced each problem for 200 rounds (r=200) under the clicking paradigm with complete feedback (FB = complete). The order of the three problems was random. The participants did not receive a description of the problems, but were informed that the experiment includes three independent parts, and when a new part starts. The final payoff for the experiment was the sum of a show-up fee of 30 Shekels and the outcome of one randomly selected trial.

Notice that Problems 1 and 2 involve a choice between alternative H, with an EV of 1 shekel, and alternative L, with an EV of 0. The higher EV maximization rate (H-rate) in Problem 1 (96%) compared to Problem 2 (58%) can be described as indication of risk or loss aversion: H was less attractive (in Problem 2) when it increased the variance and was associated with losses. However, this "risk and/or loss aversion" explanation is inconsistent with a comparison of Problem 2 and Problem 3. In Problem 3, risk aversion and loss aversion implies maximization (H choices). The results show H-rate of only 53%. Figure 3 presents the observed choice rate of H in blocks of 20 trials. It shows that the differences between the three conditions are relatively robust over time.

<Insert Figure 3>

Additional studies, reviewed in Erev and Barron (2005), demonstrate the robustness of the payoff variability effect. These studies reveal robustness to the payoff sign, to incomplete feedback, and to the number of possible outcomes. [6]

Chasing, the big eyes effect, and contingent loss aversion. One reasonable explanation of the results in Problems 1, 2 and 3 involves the assertion of large individual difference in risk attitude and/or in the attitude toward losses. For example, the aggregated results are consistent with the hypothesis that about half the participants are risk averse, and the other half are risk seekers. However, this explanation has important shortcomings. One clear shortcoming is the fact that the correlation between the R-rate in Problems 2 and 3 is not large (see Section 1.1.6). A more interesting shortcoming is suggested by studies that examine investment decisions. These studies show that investors tend to "chase" past returns (see Kliger, Levy & Sonsino, 2003; Grinblatt, Titman, & Wermers, 1995). That is, they tend to invest in assets that led to high earnings in the past. Grosskopf et al. (2006) shows that this "big eyes effect" implies that payoff variability can lead most agents to behave as if they are risk and/or loss seekers. Ben Zion et al. (2010) clarify the robustness of this observation in a study that focuses on the following problem:

[6] The payoff variability effect is related to the role of flat payoff functions. Harrison (1989) notes that the deviation from maximization (and equilibrium) observed in many experimental studies can be a product of the low expected cost of these deviations relative to the required effort to find the optimal choice. Merlo and Schotter (1992) refine this assertion and note that there may be large differences between the expected and the experienced costs. The payoff variability effect suggests that the best predictor of these deviations is the relative cost: the average cost relative the payoff variance. This suggestion is consistent with Harrison assertion under the assumption that payoff variability is one of the factors that increases the effort required to find the optimal choice.

A simplified investment problem ***(r=100, n=30, FB=complete, 1 point=¢0.25, pay rule = random trial)***

R1	4x (EV=0)	
R2	2y –2x (EV = 0)	
S	x+y+5 (the mean of R1 and R2 plus 5, EV = 5)	[S-rate = 25%]

where x is a draw from a normal distribution with a mean of 0 and standard deviation of 300 (x~N(0,300)), and y is a draw from a normal distribution with a mean of 0 and standard deviation of 10 (y~N(0,10)).

Ben Zion's et al.'s study can be described as a simulation of a simplified investment task. Options R1 and R2 simulates two risky stocks, and Option S simulates an attractive index fund that provides the mean of R1 and R2 plus a small bonus. Thus, Option S has the highest mean and lowest variance. The experiment used the clicking paradigm with complete feedback. In addition, the participants received a complete description of the payoff rule. The description emphasized the fact that S provides the mean of R1 and R2 plus 5.

The results reveal random choice in the first trial (S-rate of 33%), and a decrease in the tendency to select S with experience. That is, experience with the high payoff variability investment problem impaired maximization. The S-rate in the last block of 20 trials was only 18%. This value is much lower than the 50% rate implied by the assertion that about half of the participants are risk and/or loss averse, and lower that the 33% implied under random choice.

The correlation effect. Diederich and Busemeyer (1999) highlight an important boundary condition for the payoff variability effect. When the payoffs of the different alternatives are positively correlated, the availability of information concerning foregone payoffs eliminates the payoff variability effect. In the extreme case in which Alternative H dominates L in all trials, payoff variability has little effect.

Grosskopf, Erev and Yechiam (2006) demonstrate the robustness of this "correlation effect" in the clicking paradigm. They focused on the following two problems:

Problem 4 (r=200, n=10, FB=complete, accumulated payoffs, 10 units=.01 Shekel)

H	N(120,10) +c_t (EV = 120)	[H-rate: 75%]
L	N(100,10) +d_t (EV = 100)	

Problem 5 (same procedure as in Problem 4)

H	N(120,10) +c_t (EV = 120)	[H-rate = 98%]
L	N(100,10) +c_t (EV = 100)	

The exact payoffs were the rounded sum of two terms: A draw from a normal distribution with a mean of 100 or 120 and standard deviation of 10, and (c_t or d_t) a draw the distribution (-50 with p = 1/3; 0 with p=1/3; +50 otherwise). The values of c_t and d_t were independent. Thus the payoffs of the two alternatives are positively correlated in Problem 5, but are not correlated in Problem 4. The feedback after each trial was complete: The participants saw the obtained and the foregone payoffs. The final payoff was the sum of the obtained payoffs with the conversion rate of 1 Shekel per 1,000 points. The results show a clear correlation effect. The correlation increased the maximization rate from 75% (in Problem 4) to 98% (in Problem 5). Thus, when the correlation is high subjects can learn to maximize expected return.

Probability learning, matching and overmatching. Many of the early studies of decisions from experience used the probability learning paradigm. In each trial of a typical study the participants are asked to guess if a target light bulb will flash. The probability of a flash is kept constant throughout the experiment. Correct predictions lead to a small gain, and incorrect prediction lead to a lower payoff (0 or a small loss). Grant et al. (1951) found an almost perfect match between the true flash probability and the probability of the choice "yes" in trials 55 to 60 of their "training phase." For example, when the probability of a flash was 0.75, the proportion of "yes" choices in the last block was 75%. Notice that this behavior reflects deviation from maximization: When the probability of flash is 0.75, maximizing reinforcement requires 100% "yes" choices.

This deviation from maximization, known as "probability matching," triggered influential studies and lively debates (see Estes, 1950, 1964; Bush & Mosteller, 1955; Suppes & Atkinson, 1960; Edwards, 1961; Siegel & Goldstein, 1959; Lee, 1970; and recent analysis in Bereby-Meyer & Erev, 1998; Vulkan, 2000; Shanks, Tunney, & McCarthy, 2002). The accumulated results demonstrate that probability matching is not a steady state. That is, longer experience slowly moves choice toward maximization. It seems that behavior reflects overmatching: it falls between probability matching and maximization. In animal studies as well (e.g., Sutherland & Mackintosh, 1971; Kagel et al., 1995) the frequency with which the better alternative is chosen usually exceeds the probability of reinforcement of that alternative. These results imply that behavior in probability learning tasks can be described as an example of the payoff variability effect: When the payoff variability is large, learning is slow and the decision makers do not learn to maximize expected return.

A demonstration of the common findings using the basic clicking paradigm is provided with the study (Ert and Bereby-Meyer, in prep.) of the following problem:

Problem 6 ***(r=500, n=20, FB=complete, accumulated payoffs, 1 unit=0.01 Shekel)***

H	4 if Event E occurs 0 otherwise (EV = 2.8)	[H-rate: 90%]
L	4 if Event E does not occur 0 otherwise (EV = 1.2)	

where P(E) = .7 The observed H rate was 70% in the first 50 trials, around 90% between trial 51 and 150, and 93% between trial 401 and trial 500.

I-SAW explanation: Reliance on small samples. The payoff variability and correlation effects are captured in I-SAW with the assertion that the subjects tend to rely on small sample of past experiences (see Erev & Barron 2005, and related observation in Fiedler, 2000; Kareev, 2000; Osborne & Rubinstein, 1998).

For example, a subject that relies on a sample of 4 observations in trial t, recalls 4 past trials and selects the option that led to the best mean payoff in these trials. The expected H-rate (proportion of H choices) of this hypothetical subject is 100% in Problem 1, 69% in Problem 2 and 3, 74.6% in Problem 4, 99.8% in Problem 5, and 90% in Problem 6.

1.1.3 Underweighting of rare events and the experience-description gap

Kahneman and Tversky (1979) demonstrate that two of the best known violations of mainstream economic theory, the tendency to buy both insurance and lotteries

(Friedman & Savage, 1948), and the Allais paradox (Allais, 1953 and see a description in the next section), can be explained as indications of overweighting of rare events. Their influential analysis includes two steps: They first replicated the classical violations in a standardized experimental paradigm, and then proposed a model (prospect theory) that captures the two phenomena. Prospect theory captures the two phenomena with the assumption of a weighting function that reflects oversensitivity to rare events (events whose probability is below 0.25).

The standardized paradigm used by Kahneman and Tversky focuses on "decisions from description": The subjects were presented with a precise description of two prospects, and were asked to select (once, and without any feedback) the prospect they prefer. Barron and Erev (2003) have examined if the phenomena documented in this decisions under risk paradigm, also emerge in the clicking paradigm. Their original hypothesis was that experience will reduce the magnitude of the deviations from maximization. The results surprised them: In several of the problems that they examined, experience did not enhance maximization. In some cases experience led to a reversal of the deviations captured by prospect theory: It leads to underweighting of rare events. This pattern is known as the experience-description gap (see review in Hertwig & Erev, 2009).

Problems 7 and 8 demonstrate the evidence for underweighting of rare events in decisions from experience. These problems were studied by Nevo and Erev (2012) using the clicking paradigm with complete feedback. The participants were paid (in Shekels) for one randomly selected trial:

Problem 7 (r=100, n=24, FB=complete, payoff in shekels in a randomly selected trial)

S	0 with certainty	[S-rate = 43%]
R	+1 with probability 0.9; -10 otherwise (EV = -0.1)	

Problem 8 (same procedure as in Problem 7)

S	0 with certainty	[S-rate = 72%]
R	+10 with probability 0.1;	

	-1 otherwise (EV = +0.1)	

Notice that in Problem 7, the safer option has higher expected value, but the participants tend to select the gamble. Problem 8 reflects the opposite risk preference: The gamble has higher expected value, but the participants tend to select the safer option. As noted by Barron and Erev this pattern can be a reflection of insufficient sensitivity to the rare and extreme outcomes (the extreme outcomes that occur in 10% of the trials). Thus, the participants behave as if they believe that "it wont happen to me."

The reversed certainty effect (reversed Allais paradox). A clear demonstration of the significance of the difference between decisions from experience and decisions from description is provided by the study of variants of Allais' (1953) common ratio problems. Expected utility theory (von Neumann & Morgenstern, 1947) implies that if prospect B is preferred to A, then any probability mixture (B, p)[7] must be preferred to the mixture (A, p). In his classic research, Allais (1953) found a clear violation of this prediction. He constructed an example in which the more risky of two prospects becomes relatively more attractive when the probability of winning in both prospects is transformed by a common ratio. Kahneman and Tversky (1979) refer to this pattern as the "certainty effect." Barron and Erev (2003) demonstrate that decisions from experience (in the clicking paradigm with incomplete feedback) reflect the opposite pattern. We chose to demonstrate this effect here in a study that uses the clicking paradigm with complete feedback (this study was run by Barron & Erev but was not reported in their paper). The study considers the following problems (these problems are variants of the problems used by Kahneman and Tversky, 1979):

Problem 9 (r=400, n=24, FB=complete, accumulated payoff 1 point=.01 Shekel)

S	3 with certainty	[S-rate = 36%]
R	4 with probability 0.8; 0 otherwise (EV = 3.2)	

Problem 10 (same procedure as in Problem 9)

[7] The "Probability mixture" (B,p) means: win Prospect B with probability p; win 0 otherwise.

S	3 with probability 0.25; 0 otherwise (EV= 0.75)	[S-rate = 51%]
R	4 with probability 0.2; 0 otherwise (EV = 0.80)	

The results reveal a reversed certainty effect. The Safe option (S) was less attractive in Problem 9-- when it was associated with certainty-- than in Problem 10—when it was not. This pattern is consistent with the assertion that in decisions from experience the least likely events (probability of 0.2) are underweighted.

Additional studies of the certainty effect reveal and apparent difference between rats, bees and human subjects. MacDonald, Kagel, and Battalio (1991) show that rats exhibit the original certainty effect: They studied variants of problems 9 and 10 with payoff in caps of water, and found *more S* choices when S provides medium pay with certainty. In contrast, Shafir et al. (2008) show that honey bees exhibit the reversed certainty effect. Their study examined variants of problems 9 and 10 with payoff in term of percentage of sugar in water reward, and found *less S* choices when S provides medium pay with certainty. Shafir et al. suggest that the difference can be related to perceptual noise (rather than to a specie effect): According to this accounts the rats (but not the bees) had difficulty in discriminating the medium and high payoffs, and for that reason preferred S in the variant of Problem 9. The value of this explanation was demonstrated in a study with human subjects that reveal that a reduction of the clarity of the feedback (in a study of Problem 9 and 10) leads to the emergence of the original certainty effect.

Underweighting and overestimation. The suggestion that people underweight rare events appears to be inconsistent with previous research that demonstrates overestimation of rare events (e.g., Viscusi, 2002; Erev et al., 1994). For example Viscusi (2002) found that smokers and nonsmokers tend to overestimate the probability that smokers will develop lung cancer. Barron and Yechiam (2009) examined if this difference is mediated by different settings (e.g., clicking vs. smoking), or different tasks (deciding or estimating). They studied Problem 11 using the clicking paradigm with complete feedback, and one addition: Starting at trial 201, the participants were asked to estimate the probability of the rare outcome (1 point with probability 0.15) before each choice. The results reveal a strong tendency to prefer the risky prospect (R) in all 400 trials (mean R-rate of 79%). This result is consistent with underweighting of rare events. The estimations, on the other hand, reflected oversensitivity to rare events. The average estimate (of the 10% event) was 21%. Thus, participants appear to exhibit over-sensitivity to rare events in estimation, and under-sensitivity to rare events in choice (similar results are reported by Friedman & Massaro, 1998).

Problem 11 (r=400, n=24, FB=complete, accumulated payoffs, 1 unit=0.01 Shekel):

R	3 with probability 0.85, 1 otherwise	[R-rate = 79%]
S	2.7 with certainty	

The sampling paradigm and robustness to the number of repeated gamble realizations. Hertwig et al., (2004) note that the "experience-description gap" summarized above can be attributed to three differences between the experimental paradigms: the source of the information (experience or description), the number of repeated realizations of the gambles (one or many), and the stakes (low real payoffs, versus high hypothetical payoffs). To evaluate the role of the three factors, they examined some of the problems considered by Barron and Erev (2003) under two conditions: one-shot decisions from description, and one-shot decisions from experience.

The two conditions differed only with respect to how the decision makers learned about the options' outcomes and likelihoods. In the *description* group, options were described as in Kahneman and Tversky's studies.

In the *sampling* group, the information describing the options was not displayed. Instead, participants were shown two buttons on the computer screen and were told that each button was associated with a payoff distribution. Clicking on a given button elicited the sampling of an outcome (with replacement) from its distribution. In Problem 9, for example, drawing from one distribution led to the outcome "4" in 80% of all draws and to the outcome "0" in 20% of all draws. Sampling from the other distribution always resulted in the outcome "3". Participants could sample however often they wished. By repeatedly experiencing the contingency between choices and outcomes, participants could gradually acquire knowledge about the options' payoff structure. Once they stopped sampling, they indicated their preferred option, and, after completing all problems, participants received monetary payoffs according to their choices and the outcomes of the draws.

The observed choice proportions in the sampling group exhibit the pattern observed under the clicking paradigm. That is, the participants behave "as if" they underweight rare events. The correlation between the sampling and the clicking results was 0.92. The observed choice proportion in the description group exhibits the pattern predicted by prospect theory- the participants behave "as if" they overweight rare events. The correlation between the sampling and the description group was -0.67. These results (and similar findings reported in Weber et al. , 2004; Ungemach et al., 2008; Erev et al., 2010a; Hau et al., 2008; and in reviews by Hertwig & Erev, 2009 and Rakow & Newell, 2010) suggest that the tendency to underweight rare events in decisions from experience is not driven by the number of repeated realizations of the gambles.

Robustness to prior information. Lejarraga and Gonzalez (2011) have examined the effect of prior information of concerning the payoff distributions on the tendency to underweight rare events in the clicking paradigm. Thus, they examined the joint effect of description and experience. In one of their studies the participants were asked to select between a safe prospect that provides "3 with certainty" and a gamble that provides "64 with probability .05; and 0 otherwise." Their results reveal that the initial behavior reflects high sensitivity to the rare events, and the emergence of underweighting of rare events with experience. The proportion of gamble choice after 10 trials was below 30%. Jessup, Bishara & Busemeyer (2008) document a similar pattern in a study in which the exact value of the gamble varied from trial to trial. Alternative explanations of the weak effect of description of the incentive structure, in the current setting are discussed in Section 1.1.9 below.

Sensitivity to expected values. An extreme interpretation of the results summarized above would be to hypothesize that decision makers tend to neglect rare events; i.e., in most cases they fail to consider these events. Ert and Erev (2012) show a shortcoming of this extreme explanation by examining the following problems:

Problem 12 (r=400, n=24, FB=complete, accumulated payoffs, 1 unit=0.01 Shekel)

H	2.52 with certainty	[H-rate = 40%]
L	2.53 with probability 0.89; 2.43 otherwise	

Problem 13 (same procedure as in Problem 12)

H	2.52 with certainty	[H-rate = 72%]
L	2.53 with probability 0.89; 2.03 otherwise	

The results show a deviation from maximization consistent with underweighting of rare events in Problem 12, but not in Problem 13. This pattern suggests that the rare events are not neglected. When they are sufficiently important they are taken into account.[8]

Sensitivity to the coefficient of variance. Shafir (2000) reviews experimental studies of animal risk attitude in a binary choice task. The results suggest that under normal conditions the tendency to select the safer alternative is better predicted by the coefficient of variance (CV) than by the variance of the risky alternative. CV is defined as the payoff standard deviation divided by the payoff mean. Weber, Shafir and Blais (2004) show that this pattern is consistent with underweighting of rare events. Underweighting of rare events implies risky choices when the CV is low (relatively high mean) and risk aversion when the CV is high (relatively low mean).

Signal detection tasks. In binary signal detection tasks an observer is asked to classify stimuli that belong to one of two distributions. In a typical experiment (see review in Erev, 1998), the two distributions are normal with equal variance, and they represent the state of the world. For example, the state may be the gender of a candidate (male or female), and the signal may be the candidate's height. After each response

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[8] Additional research suggests that importance is best approximated by the difference in expected values relative to payoff variance.

(guessing male or female) the observer receives immediate payoff determined by a fixed 2x2 payoff matrix that gives the payoff for each of the four possible outcomes (correct detection of a male, correct detection of a female, incorrect male response, and incorrect female response). Assuming that the male's mean is higher, the optimal choice rule is a cutoff strategy of the type "respond male if the signal exceeds a certain height." The location of the cutoff depends on the payoff of the four outcomes and on the prior probability of the two distributions. Experimental studies of this task reveal higher sensitivity to the prior probabilities than to the payoff matrix (see Healy & Kubovy, 1981). Barkan et al., (1998) show that this pattern implies deviation from maximization in the direction of underweighting rare events.

I-SAW explanation: "sampling and weighting". The tendency to underweight rare events can be explained with the assertion, presented above, that people relay on small samples of past experiences. For example, a subject that relies on a sample of four past experiences will prefer the negative EV gamble "-10 with probability 0.1, +1 otherwise" over "0 with certainty" in 56% of the trials (because 65% of the samples of size 4 do not include the 10% event). The observed sensitivity to the expected value (Problem 13) is captured in I-SAW with the assertion that the small sample is only one of the factors that determine the attractiveness of the different alternatives. A second factor is the grand mean: The average payoff from selecting this option over all previous trials.

1.1.4 The very recent effect

Analysis of the effect of recent outcomes on choice behavior in probability learning tasks led Estes (1964, and see review in Lee, 1971) to conclude that the most common pattern is positive recency: Decision maker are more likely to select the alternative that led to the best outcome in recent trials.

A clear example of positive recency in the clicking paradigm is provided in the analysis of the contingent choice rate in Problems 2 and 3 in the top panel of Table 1. The probability of risky (R) choices is larger, in these problems, after high payoff from R than after low payoff from R. The overall R-rates are 64% after high payoff, and 40% after low payoff. Aggregation over the two payoffs (high and low) suggests that that the proportion of choices that are best reply to the most recent payoff, referred to as "Best-Reply-1" is 62%.

<Insert Table 1>

An extension of this analysis to other recent outcomes reveals an interesting pattern. To describe this pattern let Best-Reply-L be the choice rate of the alternative that led to the best outcomes exactly L trials before the current trial. Figure 4 presents the values of Best-Reply-1 to Best-Reply-20 (based on the data of trial 21 until 200 in Problems 2 and 3). The results reveal a large qualitative difference between Best-Reply-1 and the other values. The decrease in the effect of recent outcomes appears to be sharp. Best-Reply-1 reflects a strong recency effect, but Best Reply 2 and 3 are not larger than the mean value. Indeed, Best Reply 3 is the lowest point in Figure 4 curve. Nevo and Erev (2012) refer to this pattern as the "very recent effect."

I-SAW explanation: Step level sampling function. The very recent effect is captured in I-SAW with a minimal addition to the sampling and weighting assertion. The addition assumes that the most recent outcome is particularly likely to affect the next choice, while all older experiences are sampled with equal probability. One justification to this assumption is the fact that there are many natural situations in which the most recent event is most important. For example, remembering the last place in which you parked your car tends to be much more useful than remembering older parking experiences.

<Insert Figure 4>

1.1.5 Inertia and surprise-triggers-change

Analysis of the relationship between recent and current choice reveals strong positive correlation that implies inertia (see, Nevin, 1988; Cooper & Kagel, 2008; Suppes & Atkinson, 1960, Erev & Haruvy, 2005). Decision makers tend to repeat their last choice. For example, over Problems 2 and 3, the participants repeated their last choice in 68% of the trials. Moreover, inertia is a better predictor of behavior than positive recency. When inertia and positive recency leads to contradicting predictions, the participant are more likely to exhibit inertia (as noted above the proportion of a repeated R choice after low obtained payoff is only 62%).

Over-alternation. Previous research highlights two boundaries conditions of inertia. First, human decision maker exhibit over-alternation when they are ask to select between alternatives that are known to be symmetric (see Rapoport and Budescu, 1997 and Section 2.2.2 below). Second, animal studies (see review in Dember & Fowler, 1958) highlight spontaneous alternation by certain species in certain settings that can be described as response to environment in which inertia is counterproductive.

Negative recency. The first row in Table 1 presents the choice rates in Problems 7 and 8 by the last choice and the recent payoffs. The results reveal two deviations from positive recency. The first deviation emerges in Problem 8 after R choice. The rate of repeated R choice was 79% after a loss (the payoff -1), and only 61% after a gain (payoff of +10). The second indication of negative recency is observed in Problem 7 after S choice. The rate of a switch to R was 31% after a forgone loss (the payoff -10), and only 21% after a forgone gain (payoff of +1).

The lower rows in Table 1 demonstrate that this pattern is not unique to Problems 7 and 8. It presents the results obtained in the study of 12 additional problems by Nevo and Erev (using the basic clicking paradigm). Most problems reveal higher change rate after surprising outcomes even when the surprising outcomes reinforce the last choice.

The relative effect of obtained and foregone outcomes. Under an extreme interpretation of Thorndike's (1898) law of effect, behavior is driven by obtained outcomes. Thus, information concerning foregone payoffs is not likely to have a significant effect. However, experimental evaluations of this hypothesis show that it can be rejected (e.g., Mookherjee & Sopher, 1994; Camerer & Ho, 1999; Nyarko & Schotter, 2002). In fact, in certain settings people are more sensitive to foregone than to obtained outcomes (e.g., Grosskopf et al., 2006). The results, presented in Table 1, reveal a similar pattern: The best reply rate to the forgone payoff is larger than the best reply rate to the obtained payoff. One boundary condition to the current observation involves the number of alternatives. When the number of alternatives is very large people are more likely to pay attention to the payoff of the alternative they chose, than to the forgone payoff from each of the other multiple alternatives (see Ert & Erev, 2007).

I-SAW explanation: "an inertia mode, and surprise-trigger- change." The observed inertia and the complex recency pattern documented in Table 1 is captured in I-

SAW with the hypothesis that in certain trials people choose an inertia mode, and simply repeat their last choice. The probability of terminating the inertia mode increases with surprise. For example, the high rate of repeated R choices after a loss of -1 is a reflection of inertia, and the lower rate after a gain of 10 is a product of the fact that the surprising outcome (10 in this case) reduces the probability of inertia.

1.1.6 Individual differences and the Iowa gambling task

While studying patients with neuropsychological disorders Bechara, Damasio, Damasio and Anderson (1994) have found that a specific neurological syndrome is associated with poor performance in a simple decision from experience task. The population they studied was patients with lesions in the orbitofrontal cortex. This syndrome involves intact IQ and reasoning skills but poor decision-making capacities. The task they proposed for assessing decision capacities is now known as the Iowa gambling task. It is presented as a choice between four decks of cards. Each alternative results in one or two outcomes: A sure gain and some probability of a loss. The implied payoff distributions (the sum of the two outcomes) are described below:

The Iowa Gambling task:

Dis R: Win $100 with probability 0.9; lose $1150 otherwise (EV = -25)
Dis S: Win $100 with probability 0.5; lose $150 otherwise (EV = -25)
Adv R: Win $50 with probability 0.9; lose $200 otherwise (EV= +25)
Adv S: Win $50 with probability 0.5; 0 otherwise (EV = +25)

As in the clicking paradigm, the decision makers do not receive a description of the different distributions. Their information is limited to the obtained payoff after each trial. The experiment included 100 trials.

Notice that two of the alternatives are advantageous (Adv R and Adv S have expected payoff of 25), and two are disadvantageous (Dis R and Dis S have expected value of -25). Bechara et al. found that the patients with lesions in the orbitofrontal cortex did not learn to avoid the disadvantageous alternatives, while the participants in the control groups (patients with other neurological problems) did.

Following up on these findings, Busemeyer and Stout (2002) presented a simple reinforcement learning model that implies that the failure to learn in the Iowa gambling task can be a product of three different behavioral tendencies: Over-exploration, a recency effect, and insufficient sensitivity to losses. Under Busemeyer and Stout's model these three tendencies are abstracted as parameters that can be estimated from the data.

Yechiam et al. (2005; 2008) showed the value of this approach. For example, they showed that the estimation of the learning parameters can be used to distinguish between criminals. In their study of first-time offenders at the reception and classification facility for the State of Iowa Department of Corrections, diverse criminal subgroups all performed poorly in the Iowa Gambling task. However, it was found that addiction criminals, such as drug and sex criminals, showed insufficient sensitivity to losses. In contrast, more violent criminals, including those convicted of assault and/or murder, and to some extent those convicted of robbery as well, exhibited high recency.

Additional indication of the significance of individual difference is provided by the analysis of the correlation between behavior in Problems 2 and 3 in the clicking experiment described above. Recall that the experiment used the basic clicking paradigm, and 20 participants faced both problems. Following Yechiam et al. (2005) we focused on three variable: The proportion of risky choices (a measure of attitude toward losses), the proportion of "Best reply-1 (a measure of a recency effect), and the distance between the mean choice rate and 0.5 (a measure of decisiveness). The observed correlations are 0.18, 0.75, and 0.69 for loss attitude, recency, and decisiveness (and the last two values are highly significant).

I-SAW explanation: distributions of traits. I-SAW assumes that the observed individual differences reflect quantitative rather qualitative differences. That is, the different tendencies can be captured as indications of individual specific learning parameters. In addition, I-SAW distinguishes between two classes of parameters. One class involves the parameters that describe individual agents; we refer to these individual parameters as "traits." A second class involves the parameters that capture the distribution of traits in the population. In the analysis present below we reduce the number of free parameters by estimating the population parameters and assuming that the traits are randomly sampled from the distribution implied by these parameters.

1.1.7 Quantitative summary: Inertia, Sampling and Weighting (I-SAW)

Nevo and Erev (2012) propose a descriptive model that can reproduce the six behavioral regularities reviewed above. The model is a joint quantification of the "I-SAW explanations" presented above. It can be described by the following assumptions:

I-SAW1. Three response modes: The model distinguishes between three response modes: exploration, exploitation and inertia. Exploration is assumed to imply random choice. The probability of exploration, by individual i, is 1 in the first trial, and ε_i (a trait of i) in all other trials.

During exploitation trials, individual i selects the alternative with the highest Estimated Subjective Value (ESV). The ESV of alternative j in trial $t > 1$ is:

$$ESV(j,t) = (1-w_i)(S\_Mean) + w_i(G\_Mean) \quad (1)$$

where S_Mean (sample mean) is the average payoff from Alternative j in a small sample of μ_i previous experiences (trials) in similar settings, G_Mean (grand mean) is the average payoff from j over all (t-1) previous trials, and μ_i and w_i are traits.

The assumed reliance on a small sample of experiences was introduced to capture underweighting of rare events and the payoff variability effect (see similar abstractions in and related ideas in Osborne & Rubinstein, 1998; Fiedler, 2000; Kareev, 2000, Rapoport & Budescu, 1997, and Hertwig et al., 2004; Lebiere, Gonzalez & Martin, 2007). The assumed sensitivity to the grand mean was introduced (following a similar assumption in Gonzalez et al., 2003) to capture the observed sensitivity to expected values.

I-SAW2. Similarity and recency: The μ_i draws are assumed to be independent (sampling with replacement) and biased toward the most recent experience (Trial t-1). A bias occurs with probability ρ_i (a trait) and implies draw of Trial t-1. When a bias does not occur (probability $1-\rho_i$) all previous trials are equally likely to be sampled. The motivation behind this assumption is the "very recent effect."

I-SAW3. Surprise-triggers-change: Inertia is added with the assumption that the individuals tend to repeat their last choice. The exact probability of inertia at trial t+1 is assumed to decrease when the recent outcomes are surprising. Specifically, if the exploration mode was not selected, the probability of inertia is:

$$P(Inertia\ at\ t+1) = \pi_i^{Surprise(t)} \quad (2)$$

where $0 \leq \pi_i < 1$ is a trait that captures the tendency for inertia. The value of the surprise term is assumed to equal the average of four gaps between certain expectations and the obtained payoffs. In the first two (one per alternatives) the assumed expectation is that the last payoffs will be obtained again; thus the gap is between the payoff at t-1 and the payoff at t. In the last two the assumed expectation is the mean payoff; thus, the gap is between the grand mean and the payoff at t. Specifically,

$$Gap(t) = \frac{1}{4}\left[\sum_{j=1}^{2}\left|obtained_j(t-1) - Obtained_j(t)\right| + \sum_{j=1}^{2}\left|G\_mean_j(t) - Obtained_j(t)\right|\right] \quad (3)$$

where $Obtained_j(t)$ is the payoff obtained from j at trial t, and $G\_mean_j(t)$ is the average payoff obtained from j in the first t-1 trials (the grand mean). The surprise at t is normalized by the mean gap (in the first t-1 trials):

$$Surprise(t) = Gap(t)/[Mean\_Gap(t) + Gap(t)] \quad (4)$$

The mean gap at t is a running average of the gap in the previous trials (with Mean_Gap(1) = .00001). Specifically,

$$Mean\_Gap(t+1) = Mean\_Gap(t)(1-1/r) + Gap(t)(1/r) \quad (5)$$

where r is the expected number of trials in the experiment (100 in the current study).

Notice that the normalization (Equation 4) implies that the value of *Surprise(t)* is between 0 and 1, and the probability if inertia is between π_i (when *Surprise(t) =1*) and 1 (when *Surprise(t) = 0*). An interesting justification for this gap-based abstraction comes from the observation that the activity of certain dopamine related neurons is correlated with the difference between expected and obtained outcomes (see Schultz, 1998; and related analysis in Caplin & Dean, 2007).

I-SAW4. Individual differences, traits, and parameters: The traits are assumed to be independently drawn from a uniform distribution between the minimal possible value (allowed by the model) and a higher point. Thus, the model has five free parameters: the highest point of the five distributions.

Estimation and results. We used a grid search procedure to estimate the parameters of the model. The criterion was the Mean Squared Deviation (MSD) between the model's predictions and the experimental results (including the results summarized in Table 1). That is, we ran computer simulations to derive the prediction of the models under different parameters, and selected the parameters that minimize the MSD score. The estimated parameters imply the following trait distribution: ε_i~U[0,.24], w_i~U[0,1], ρ_i~U[0,.12], π_i~U[0,.6], and μ_i = 1, 2, 3 or 4 .

The right-hand columns in Table 1 present the predictions of I-SAW with these parameters. The results reveal that I-SAW reproduces all the behavioral tendencies documented in Table 1. In addition, the model provides good quantitative fit. For example, the correlation between the predicted and the observed aggregated choice rates is 0.9, and the MSD score is 0.007. Additional evaluations of this model are discussed in Sections 1.3 and 2.2 below.

1.1.8 Implications to traditional reinforcement learning and fictitious play models.

I-SAW can be described as an example of a reinforcement learning model (see Satton & Barto, 1998; Erev & Roth, 1995), and as a generalization of the Fictitious Play rule (Brown, 1951; Robinson; 1951 and see Fudenberg & Levine, 1998). The following section clarifies these related connections.

Fictitious play (FP). The FP rule assumes that the decision maker tries to maximize expected return under the assumption that the payoff distributions are static. This assumption is fictitious in many settings, but it is correct in the basic clicking paradigm. At trial t >1 this rule implies a selection of the alternative that led to the highest average payoff in the first t-1 trials (and random choice is assumed at t=1). I-SAW implies FP with the traits: ε_i=0, w_i=1, ρ_i= 0, and π_i=0. That is, under the FP rule, the estimated subjective value is the grand mean (G_Mean), and the alternative with the highest G_Mean is selected. The correlation between the aggregated choice rate and the model with these parameters is 0.76 and the MSD score is 0.039. These results suggest that the FP rule (and the implied maximization assumption) provides useful approximation of the results, but the I-SAW generalization of this rule provides a much better approximation. Additional analysis reveals that the advantage of the generalized model over the FP rule decreases when the difference between the average payoffs from the different alternative is large (relatively to the payoff variability); when this relative difference is large enough the predictions of I-SAW are identical to the predictions of the FP rule.

Stochastic Fictitious play (SFP). The SFP model (Cheung & Friedman, 1997, 1998) is a generalization of the FP rule that allows for the possibility that the estimated subjective value of option j at trial t includes error. That is:

$$ESV(j,t) = G\_Mean(j,t) + \varepsilon_{jt} \qquad (6)$$

The traditional implementation adds the assumption that the error terms are randomly, identically and independently distributed. It is convenient to assume that this distribution follows Type I Extreme Value Distribution, which approximates the normal distribution. As demonstrated by McFadden (1974) this assumption implies that the probability of preferring j over k at trial t is

$$P(j,t) = 1/(1+e^{\sigma[G\_Mean(k,t)-G\_Mean(j,t)]}) \qquad (7)$$

SFP can be described as a variant of I-SAW with the parameters ε_i=0, w_i=.5, ρ_i= 0, π_i=0, and with a modified error term. The error term under I-SAW is determined by a draw of μ_i past experiences. The I-SAW error term is less convenient to modelists (as it does not allow the derivation of the elegant choice probability term implied under normal error), but it appears to fit the data better. The advantage of the I-SAW error term is clarified by a comparison of Problem 1 and 2. I-SAW implies no error in Problem 1 (the trivial no variability problem), and high error rate in Problem 2. The SFP allows for the possibility of different error term by assuming situation specific σ values, but cannot predict a long-term difference between the two problems without problem specific parameters.

Reinforcement learning. Simple reinforcement learning models were found to provide good ex-ante predictions of behavior in certain games (Erev & Roth, 1998), to imply maximization in certain settings (Sutton & Barto, 1998), and to be consistent with known activities of the brain (Schultz, 1998). In order to clarify the relationship of these models to the current results it is important to recall that the term "reinforcement learning" is used to describe a very large set of models (Dayan & Niv, 2008). I-SAW is a member of this class of model. We believe that the most important difference between I-SAW and the popular reinforcement learning model involves the "error term" discussed above. Like the SFP model, the popular reinforcement learning models assume a normal error term. Other differences between I-SAW and the popular reinforcement learning models involve the surprise trigger change assumption, and the abstraction of the recency effect. The new assumptions were introduced to capture the six phenomena summarized in Section 1.1, and are evaluated in the two choice prediction competitions described in Section 1.3.

Probability Matching. The probability matching rule implies that the decision makers will match their choice rate to the proportion of time that the prospect is the best choice (see Estes, 1950). Under a natural cognitive implementation of this idea it implies the following choice rule: On each trial the decision maker samples one outcome from the payoff distributions of each alternative, and selects the alternative with the highest drawn outcome (random choice is assumed in the first trial and in the case of a tie). Blavatskyy (2006) demonstrates that this simple idea captures the typical behavior in Barron and Erev's demonstration of the payoff variability effect and underweighting of rare events. However, as noted by Erev and Barron (2005) the probability matching rule over predicts underweighting of rare events, and the payoff variability. I-SAW implies probability matching with the traits ε_i=0, w_i=0, ρ_i= 0, and π_i=0, and μ_i = 1. The correlation between the aggregated choice rate and the model with these parameters is 0.56 and the MSD score is 0.130.

1.1.9 Alternative explanations of the experience-description gap.

Prospect theory (Kahneman & Tversky, 1979; Wakker, 2010), the leading model of description from description, captures three main behavioral regularities: Overweighting of rare events, loss aversion, and the reflection effect (risk aversion in the gain domain, and risk seeking in the loss domain). The results reviewed above show that different regularities emerge in the study of decisions from experience. The results reflect underweighting of rare events (Section 1.1.3), and no indication for loss aversion (Section 1.1.2). In addition, under certain settings decisions from experience reveal a reversed reflection effect (Ludvig & Spetch, 2011).

Recent research suggests several contributors and explanations to these differences. Our favorite explanation involves the assertion that decisions from description are a subclass of the larger class of decisions from experience. As in other subclasses, the decision makers tend to select strategies that have led to good outcomes in similar situation in the past. The experience-description gap emerges, under this explanation, as a result of two main effects of the available description. First, in certain cases, the description affects the set of strategies that can be used (see related ideas in Busemeyer & Myung, 1992; Erev, 1998; Rieskamp & Otto, 2006; Erev & Roth, 2001; Stahl, 2000; Erev & Barron, 2005). Second, the description affects the set of past experiences perceived to be similar.

In order to clarify the assertion that the description can affect the set of strategies, consider the following hypothetical choice problem:

Thought Experiment 1. Choose between:

H	0 with certainty
L	$1 with probability .99, -$1,000,000 otherwise

It is easy to see that the availability of a description of the incentive structure will have a large effect here. Without a description (if this problem would be studied using the basic clicking paradigm) people are likely to select L at least until the first loss. With a description, reasonable individuals are expected to prefer H. We believe that this pattern can be captured with the assertion that the current description leads people to follow "compute the expected values implied by the description, and select the best alternative based on this dimension." The apparent inconsistency between this assertion and the weak effect of description discussed in Sections 1.1.2 and 1.1.3 can be explained with the assertion that the tendency to use the EV rule decreases when the difference between the expected values, implied by the description, appear to be small and/or when the computation is too difficult (see Payne Battman and Johnson, 1993) . That is, the EV strategy is less likely to be used when the problem is similar to problems in which the EV rule was not found to be effective.

Marchiori et al. (2012) show that the current assertion can be used to explain "overweighting of rare events" in "one-shot decisions from description." Their explanation adds the assumption of overgeneralization from situations in which people decide based on subjective probability estimates. Subjective probability estimates tend to reflect overconfidence; for example, studies of probability estimates reveal that event estimated by "5%" occur in about 20% of the times (Erev, Wallsten & Budescu, 1994). Thus, overweighting the 5% outcome tends to be reinforcing. Experience eliminates this bias, and can lead to the opposite bias.

Other likely contributors to the differences between the basic properties of decisions from experience and the predictions of prospect theory are presented below.

The White Bear effect and the weighting of rare events. Wegner et al., (1987) note that when we "try not to think about a white bear," a white bear comes to our mind. This "white bear effect" can be one of the contributors to the tendency to overweight rare events in decisions from description. For example, it is possible that the gamble "5000 with probability 1/1000, and 0 otherwise" seems attractive because we cannot avoid paying too much of their attention to the outcome 5000 (see Birnbaum & Martin, 2003). Underweighting of rare events in decisions from experience emerges, under this logic, because the availability of feedback reduces the attention given to the description and leads the subjects to focus on the experienced outcome (Erev, Glozman & Hertwig, 2008).

Contingent loss aversion. The loss aversion assertion, one of the cornerstones of prospect theory (Kahneman & Tversky, 1979), states that losses loom larger then gains. Thus, it predicts that when selecting among mixed prospects (prospects that can yield both gains and losses) people often prefer the safer asserts over riskier assets with higher expected value. The simplified investment problem, examined in Section 1.1.2 reveals the opposite bias: A tendency to prefer the risky prospects even though the safe option has provides higher expected return.

Under one explanation of this deviation from loss aversion, it reflects an "experience-description gap in the reaction to losses." This explanation is plausible, but it has two shortcomings. First, there many situations in which people do not exhibit loss aversion in decisions from description (see Ert & Erev, 2008, 2012, and the first trial in the simplified investment problem). Most importantly, people appear to exhibit equal sensitivity to gains and loss in decisions from description when the payoff magnitude is low. Thus, it is possible that small losses have similar effect on decisions from experience and from description. And the typical behavior, in both classes of decisions, reflects less loss aversion than implied by prospect theory (the prediction of prospect theory do not depend on the payoff magnitude).

A second shortcoming of the assumed experience-description gap in the current setting is the observation that certain presentations of the outcomes can lead to behavior that appears to reflect loss aversion in decisions from experience (See Thaler et al., 1997; and a clarification in Erev et al., 2008). For example, when people are asked to select between a "sure gain with certainty" or "risky prospect that provides higher expected return but often leads to a loss" they exhibit loss aversion when the payoffs are presented graphically, but not when they are presented with clear numbers.

1.2 The effect of limited feedback

Many natural decisions from experience problems involve situations in which the feedback is limited to the obtained payoffs. For example, when we choose to order a certain dish in a restaurant we are not likely to know the outcome of ordering a different dish. The current section explores these decision problems with a focus on experiments that use the clicking paradigm (Figure 1) with limited feedback. That is, the feedback provided after each trial is limited to the outcome of the selected key.

Experimental studies that examine this set of "limited feedback" situations highlight the generality of the six phenomena listed above. Yet, the results also demonstrate the nature of the feedback can change the magnitude of the basic phenomena. The main changes can be described as reflections of the hot stove effect described below.

1.2.1 The hot stove effect

Mark Twain (1897) asserts that after sitting on a hot stove lid, a cat is likely to avoid sitting on stove lids even when they are cold. Denrell and March (2001; also see Denrell, 2005; Denrell, 2007, and a related observation in Einhorn & Hogarth, 1978) show that Twain's assertion is a likely consequence of learning when the feedback is limited to the obtained payoff. Learning in this setting increases risk aversion. This observation, referred to as the hot stove effect, is a logical consequence of the inherent asymmetry between the effect of good and bad experiences. Good outcomes increase the probability that a choice will be repeated and for that reason facilitate the collection of additional information concerning the value of the alternative that has yielded the good outcome. Bad outcomes reduce the probability that the choice will be repeated, and for that reason impair the collection of additional information concerning the value of the alternative that has yielded the bad outcome. As a result, the effect of bad outcomes is stronger (lasts longer) than the effect of good outcomes. Since options with a high variability are more likely to produce bad outcomes, the hot stove hypothesis predicts a decreasing tendency to choose such options.

One indication of the descriptive value of hot stove effect is provided by a comparison of choice behavior with and without foregone payoffs in the four-alternative Iowa Gambling task discussed above. The availability of foregone payoffs tends to increase risk taking (see Yechiam & Busemeyer, 2006). A similar pattern was documented by Fujikawa (2010) in an analysis of Problem 9. His analysis suggests that the hot stove effect can reduce underweighting of negative rare events.

Additional experimental studies demonstrate that the magnitude of the hot stove effect is maximal when the risky alternative is a long shot gamble. Table 2 illustrates this pattern. It presents the proportion of R choice in 12 problems that were run for 100 trials using the basic clicking paradigm (with complete feedback), and a variant of the clicking with and without forgone payoffs (the limited feedback condition were run by Erev et al. 2010, and the complete feedback conditions were run by Nevo & Erev, 2012). The results (presented in two blocks of 50 trials) reveal a large hot stove effect in "rare treasure" problems when the probability of a high payoff from risky choice is 0.1 or lower: In all seven problems of this type, the R-rate in the last block is higher in the complete feedback condition. The pattern in the five problems with higher probability of high payoff from risky choice is less clear.

<Insert Table 2>

Diminishing exploration. As noted above, the existence hot stove effect is implied by all models that assume positive recency. The interaction of the observed effect, with time, and with the magnitude of high payoff from the risky option is more informative. The most natural explanation of the observation that the effect increases with time (from the first to the second block) can be captured with the assertion of diminishing exploration: High exploration rate in the beginning of the experimental session, and lower rate of exploration toward the end.

The observation that the hot stove effect was not observed in the problems in which the risky prospect leads to good outcome most of the time can be the product of the fact that even limited exploration is enough, in these cases, to demonstrate the value of the risky option. If some exploration continues even after an extreme low payoff, the hot stove effect is not likely to emerge. This explanation is captured in I-SAW and similar models with the assumption that the probability of exploration is independent on the obtained payoffs.

Two-armed bandit problems. The task faced by the subjects in the limited feedback condition of summarized in Table 2 is similar to 2-armed bandit problem (see Degroot, 1970; Gittins, 1989). Yet, the common analyses of 2-armed bandit problem focus on situations in which the decisions makers have more information, and the optimal strategy can be computed. Specifically, they know the expected payoff from the safe option, and know that the risky option provides one of two outcomes with fixed probability. Theoretical analysis of these 2-armed bandit problems reveal that the optimal strategy is to start with exploration of the risky option, and switch to the safe option if the outcomes fall below a certain cutoff. Thus, the diminishing exploration pattern suggested here is similar to the optimal strategy in these simpler problems.

Direct experimental studies of 2-armed bandit problems show the robustness of the pattern discussed above. Meyer and Shi (1995) results reveal an increase in counterproductive exploration with payoff variability, and a slow reduction in exploration (not enough exploration in the beginning, and to much exploration in the end). Gans, Knox and Croson (2006) results suggest large individual differences, and a very recent effect.

1.2.2 I-SAW with diminishing exploration.

Erev, Ert and Yechiam (2008) show that the main properties of binary decisions from experience with limited feedback can be captured with an "exploration sampler" model that assumes reliance on small samples, and diminishing exploration. The main assumptions of this model can be captured in an extension of I-SAW (Section 1.1.7) that adds the assumption that the probability of exploration depends on the available feedback. I-SAW assumes that when the feedback is complete (include information concerning obtained and forgone payoff), the probability of exploration is fixed during the experiment and reflect an individual trait (ε_i). The extended version adds the assumption that when the feedback is limited to the obtained payoff, the probability of exploration starts at 1, and diminishes with time. The speed of the decline in exploration is assumed to depend in the expected length of the experiment. Specifically, we assume that when the probability of exploration at trial t equal $\varepsilon_i^{\frac{t-1}{T}}$ where T is the length of the experiment (in the experiments reviewed in Table 2, T= 100). In addition, the extension of I-SAW to situations with limited feedback implies that less information is used during sampling and during the computation of surprised: only the observed obtained payoffs are used.

1.3 Two choice prediction competitions

We believe that the basic learning phenomena, considered above, are an important part of the phenomena that determine the shaping of human behavior by the incentive structure. This optimistic assumption implies that good models of the joint effect of these phenomena can provide useful ex-ante predictions of the effect of economic incentives in a wide set of situations (Erev & Roth, 1998). Two choice prediction competitions that evaluate this optimistic assertion, and facilitate the comparison of alternative learning models are described below.

1.3.1 The Technion prediction tournament: Individual decisions with limited feedback

Erev et al. (2010a) present a choice prediction competition designed to facilitate the development and comparison of models of decisions from experience under limited feedback.[9] The organizers of the competition (the first three co-authors of that paper) run two large experimental studies using the clicking paradigm without information concerning forgone payoffs. Each study focused on 60 randomly selected problems. All the problems involved a choice between a safe prospect that provides a medium payoff (referred to as M) with certainty, and a risky prospect that yields a high payoff (H) with probability Ph, and a low payoff (L) otherwise. Thus, the basic choice problem is:

S: M with certainty

R: H with probability Ph; L otherwise (with probability 1-Ph)

The four parameters (M, H, Ph and L) were randomly selected with a well defined algorithm that implies: (1) The possible payoffs were between -30 and +30 Shekels (1 Shekel equaled about $0.3); (2) L < H; (3) M was between L and H in 95% of the problems; and (4) the difference between the expected values of the two prospects was relatively small. Twelve of the 120 problems that were examined are presented in Table 2.

[9] In addition to this competition, Erev et al. organized a competition that focuses on decision from description, and a competition that focuses on decisions based on free sampling. The comparison of the three competitions clarifies the robustness of the experience-description gap.

The first study, referred to as the estimation experiment, was run in March 2008. Each of the 60 problems was faced by 20 subjects for 100 trials. Each subject played 12 games, and the payoffs (in Shekels) were determined by a randomly selected trial. In April 2008 the organizers posted the result and the best baseline models that they could find on the web (see http://tx.technion.ac.il/~erev/Comp/Comp.html) and challenged other researchers to predict the results of the second study. The second study, referred to as the competition experiment, was run in May 2008 using the same experimental method as the estimation experiment but different randomly selected problems and different subjects. The results of the competition study were not revealed until Septemeber 2nd 2008.

Researchers participating in the competitions were allowed to study the results of the estimation study. Their goal was to develop a model that would predict the results (the mean choice proportion over all choices in each problem) of the competition study. The model had to be implemented in a computer program that reads the payoff distributions of the relevant gambles as an input and predicts the proportion of risky choices as an output. The submission deadline was Septenber 1st 2008. The submitted models were ranked based on the Mean Squared Deviation (MSD) between the predicted and the observed choice proportions.

ENO (Equivalent Number of Observations). One advantage of the MSD criteria used here is its relationship to traditional statistics (like regression, t-test and the d-statistic) and its intuitive interpretation. These attractive features are clarified with the computation of the ENO (Equivalent Number of Observations) order-maintaining transformation of the MSD scores (see Erev et al., 2007). The ENO of a model is an estimation of the size of the experiment that has to be run to obtain predictions that are more accurate than the model's prediction. For example, if a model's prediction of the probability of risky choices in a particular problem has an ENO of 10, this prediction is expected to be as accurate as the prediction based on the observed proportion of risky choices in an experimental study of that problem with 10 participants.

Results. The models evaluated in the competition can be classified in two main classes: The first includes instance-based models like I-SAW that assume reliance on small samples of experiences. The second include models like reinforcement learning with a normal error terms that do not assume memory of and/or reliance on specific experiences. About half of the baseline models and half of the submissions belong to each class. The results reveal a large advantage of the instance-based models. The best baseline model was a predecessor of I-SAW. The ENO of this best baseline was 47.2. In the current context the predictions of this model are almost identical to the predictions of the refined model, I-SAW, with the parameters : ε_i~U[0,.20], w_i~U[0,1], ρ_i~U[0,.6], π_i~U[0,.6], and μ_i drawn from integers 1 to 14.

The winner of the competition was an instance-based model that assumes an ACT-R[10] cognitive architecture (submitted by Stewart, West and Lebiere). Like the best baseline and I-SAW, the winning model builds on the instance based learning model proposed by Gonzalez et al. (2003) and implies reliance on small samples of experiences. The winner had slightly lower ENO (32.5) than the best baseline (the baseline models did not participate in the competition), but it has two attractive features. First, the ACT-R cognitive architecture involves a psychologically more realistic abstraction of the relevant memory processes. For example, the instance based model assumes a continuous weighting of all past experiences. Second, the instance based model was designed to capture decisions in dynamic environments. We return to this point below.

Analysis of the predictions of reinforcement learning models assuming "normal error term" that participated in the competition suggests that their most important failure involves the effect of Ph (the probability of high payoff from risky choice). With the parameters that best fit the data, these models under-predict the R-rate (over-predict the hot stove effect) with high Ph values, and over-predict the R-rate with low Ph. This pattern appears to be a result of the fact that these models imply that an extreme low payoff from the risky prospect decreases the probability of future exploration of this prospect.

Another outcome that emerges from the evaluation of the submission to the competitions involves the estimation technique: all the leading submissions were used a "computer simulation based estimation method," and did not use more sophisticated, one-period-ahead, econometrics technics. This observation appears to be surprising as

[10] ACT-R (Adaptive Control of Thought—Rational) is general theory of cognition (see Anderson & Lebiere, 1998).

previous research shows that when the model is "well-specified," the correct one-period estimation provides best estimate of the parameter. One explanation of this observation suggests that the current models are miss-specified, and the one-period-ahead techniques are more sensitive to this miss-specification (see Erev & Haruvy, 2005).

1.3.2 The Market Entry game competition: Social interaction with complete feedback.

Erev et al. (2010b) organized a choice prediction competition that focuses on 4-person market entry games under limited prior information. The experimental subjects were informed that they play a market entry game, and have to select between a risky entry to the market and a safer decision to stay outside the market.

The payoffs depended on a realization of a binary gamble (the realization at trial t is denoted G_t, and yields "H with probability Ph; and L otherwise"), the number of entrants (E), and two additional parameters (k and S). The exact payoff for player i at trial t was:

$$V_i(t) = \begin{cases} 10 - \mathrm{k(E)} + \mathrm{G_t} & \text{if i enters} \\ \mathrm{round(G_t/S)} \text{ with } p = .5; -\mathrm{round(G_t/S)} \text{ otherwise} & \text{if i does not enter} \end{cases}$$

The parameters H, Ph, L, k and S where randomly drawn under certain constraints (e.g., the expected value of the gamble was zero, the mean entry rate at equilibrium was 0.5).

The participants did not receive a description of the payoff rule, and had to rely on a complete feedback (obtained and forgone payoffs) after each trial. The organizers run an estimation study with 40 games, and a competition study with 40 additional games.

The results of the estimation study were published in May 2010, and the submission deadline was September 2010. The analysis of the estimation study suggests that results exhibit the basic learning phenomena documented in individual choice task and summarized in section 1.1. In addition, the result show high initial entry rate: 66% in the first trial. Comparison of several baseline models highlights the advantage of I-SAW over other models. Best fit was provided with a slight modification of the "strategy set simplification assumption": The best baseline model is I-SAW with the assumption of an initial tendency to entry the marker in 66% of the trials.

Twenty-five teams participated in the competition. The submitted models included reinforcement learning, neural networks, ACT-R, and I-SAW like sampling models. The results reveal a large advantage of sampling models that assume reliance on small samples and surprise-triggers-change. Indeed, all the ten leading submissions belong to this class of models. The winner of the competition (Chen et al., 2011) is a variant of I-SAW that adds the assumption of bounded memory. The runner up (Gonzalez et al., 2011) quantifies the similar assumptions in a refinement of the instance based learning model (Gonzalez et al., 2003).

The ENO of I-SAW (in predicting the average payoff, a statistic that captures the entry rate and implied coordination level) in the last block of 25 trials was 42.2. As in the first competition, traditional "normal error term" reinforcement learning models did not do well. It seems that the main reason for their failure here involves the co-existence of "underweighting of rare events" and relatively weak recency effect. The traditional reinforcement learning models (and the similar fictitious play and experience weighted attraction, Camerer & Ho, 1999) that were evaluated have to assume a strong recency effect in order to capture the observed underweighting of rare events.

Another similarity to the first competition involves the estimation techniques used by the best models. All the top submissions used simulation-based methods and avoid more sophisticated one-period-econometrics.

2. Dynamic environments and multiple alternatives

Many of the early experimental studies of learning focused on the effect of training in one environment (the training phase) on performance in another environment (test phase). Thus, they examined decisions in dynamic environments. In addition, many of these studies focused on situations in which the number of strategies is large. Some of the classical results documented in these settings are reviewed below.

2.1 Successive approximations, hill climbing and the neighborhood effect

Skinner (1938) highlights the value of the "method of successive approximations" (also known as "shaping") for teaching complex behavior. Shaping is used when the desired behavior is not observed initially. The procedure involves first reinforcing some observed behavior only vaguely similar to the one desired. Once that behavior is established, the trainer looks for (reinforces) variations that come a little closer to the desired behavior, and so on. Skinner and his students have been quite successful in teaching simple animals to do some quite extraordinary things. For example, they taught a pigeon to control a missile (Glines, 2005).

The basic idea behind the method of successive approximations is the assumption that there are many strategies that can be used in an attempt to perform a complex task. That is, the set of feasible strategies is very large. The agent tends to consider strategies similar to the reinforced strategies. As a result, learning does not insure convergence to the globally optimal strategy. It can lead to a local optimum. The method of successive approximations is effective because it reduces this risk (at least when the trainer has a good understanding of the location of the optimal strategy).

A clear demonstration of the tendency to converge to a local optimum is provided by Busemeyer and Myung's (1988) examination of choice behavior in a multiple alternative resource allocation task. In each trial the participants were asked to divide limited resources among three issues. Each allocation can be abstracted as a selection of one of many possible allocations (strategies) that can be placed in a triangle (called the simplex). The results reveal that performance is highly sensitive to the location of the different strategies in the simplex. Higher maximization rate was observed when the best strategies were in the same "neighborhood." Busemeyer and Myung (1988) note that this regularity can be captured by a hill climbing search process.

Erev and Barron (2002) replicated this observation in a study that focused on Problems 26 and 27 using the clicking paradigm with limited feedback. Both problems involve a choice among the same 400 alternatives. Each alternative is associated with only one outcome. The two problems differ with respect to the location of the 400 alternatives in the 20X20 matrix presentation. The top panel in Figure 5 shows a three-dimensional summary of the two matrices. It shows that both matrices have two maximum points (a local maximum of 32 and a global maximum of 52). The conversion rate was ¢0.25 per point. In Problem 26 the local maximum (32) had a wide basin of attraction. Problem 27 was created by swapping the location of the two maxima; thus, the global maximum (52) had the wide basin of attraction.

<Insert Figure 5>

The lower panel in Figure 5 presents the proportion of maximization under the two conditions. In line with Busemeyer and Myung's findings, the decision makers were closer to maximization in Problem 27 (global maximum with wide basin of attraction) than in Problem 26. Since maximization rate seems to depend on the relative location of the global maximum we refer to this result as the "neighborhood effect." Yechiam et al. (2001) clarify the relationship between convergence to local optimum and shaping. They show that a minimalistic shaping procedure, the prevention of repeated choice, reduces the tendency to converge to a local maximum in a variant of Problem 26.

Implications to descriptive models. The attempt to model learning among multiple alternatives given incomplete feedback highlights the importance of the details of the assumed exploration process. Busemeyer and Myung (1988) show that the main features of the exploration process can be captured with a hill climbing rule. Erev and Barron (2002, and Yechiam et al., 2001) show the value of modeling hill climbing as one of several cognitive strategies. The model assumes reinforcement learning among these strategies. Rieskamp et al. (2003) highlight the value of a model that assumes a focus on the difference between the current results and the best past experience.

Analyses of exploration by firms (Levinthal & March, 1993; Gavetti & Levinthal, 2000) highlight the value of a distinction between two types of exploration: forward looking, and backward looking. Teoderscu and Erev (2012) demonstrate the value of this distinction in capturing the results of experimental studies of choice behavior among multiple alternatives using the clicking paradigm. Their results reflect insufficient exploration in "rare treasure problems" (when the common outcome of exploration is disappointing), and over-exploration in rare mines problem (when the common outcome of exploration is attractive). These results can be captured with an extension of I-SAW that assumes a choice between cognitive strategies (exploration or exploration) before the choice between the actions.

2.2. Multiple alternatives with complete feedback

An increase in the number of possible alternatives increases the importance of the availability of information concerning the forgone payoffs. When the payoff variability is low, the availability of complete feedback facilitates maximization and leads to very quick learning to prefer to best option (Grosskopf et al., 2006). However, when the payoff variability is large, the availability of complete feedback can lead to the big eyes affect (see Section 1.1.2) that can impair maximization.

Ert and Erev (2007) examined a 50 alternative problem (using the clicking paradigm with forgone payoff) in which the predictions of the big eyes effect contradicts the predictions of underweighting of rare events. Half of the 50 alternatives provided 3 with certainty, and the other half provided 32 in 10% of the trials, and 0 otherwise. Thus, the risky option maximized expected value, and the big eye effect implies risky choice (because the best outcome over the 50 alternatives tends to be 32 from one of the risky alternatives). The choice rate of the risky option (after 50 trials) was only 40%. It seems that in the current setting underweighting of rare event is stronger than the big eyes effect. This pattern can be captured with the assertion that regret reduces payoff sensitivity. Another explanation assumes limited attention. Specifically, it is reasonable to assume that when the number of alternative is very large people cannot attend to all the forgone payoffs (see related idea in Camerer & Ho, 1999).

2.3 Spontaneous alternation, the gambler fallacy and response to patterns

Tolman (1925) observed an interesting violation of the law of effect in a study of rats' behavior in a T-maze. Upon receiving a reinforcement in a particular arm, rats tend to switch to the other arm of the maze. According to the common explanation to this spontaneous alternation pattern (see review in Dember & Fowler, 1958), it reflects a tendency to respond to the likely sequential dependencies in natural settings. That is, in most environments where rats eat (e.g., storehouses and garbage dumps) food is replenished independently of feeding. Thus, after eating the food in one location, it is typically optimal to move to a different location.

More recent studies (see Estes, 1976; Sonsino, 1997) use a similar argument to explain the large effect of payoff variability on learning. These studies suggest that the payoff variability effect can be a result of an effort to respond to patterns and sequential dependencies in the environment. When the environment is static and noisy, this effect impairs maximization. When the environment changes in a consistent fashion, sensitivity to sequential dependencies can be very useful (see e.g., Gonzalez et al., 2003; Sterman, 1989). Biele, Erev and Ert (2009) examined how people adjust to dynamic environments by considering the following problem:

Problem 28 (r=300, n=24, FB=obtained, 1 point=.01 shekel)

S	0 with certainty
R	+1 if the state is H -1 if the state is L

The decision maker in this problem is required to choose between a safe prospect (S) that maintains the status quo, and a risky prospect (R), whose payoff depends on the state of nature. The exact state is determined using the Markov process presented in Table 3.

<Insert Table 3>

Table 3 implies that the environment is dynamic. The payoff distribution associated with Alternative R changes over time. The nature of this dynamic is determined by the two transition probabilities: p and q. Biele et al. (2009) studied two variants of Problem 33 using the clicking paradigm. The variants involved a symmetric transition matrix with q=1-p, and differed with respect to the value of p. The values were p=.95 (positive recency), and p=0.5 (no recency).

The main experimental results are summarized in Figure 6. They reflect clear sensitivity to the dynamic nature of the environment. For example, the participants learned to repeat risky choices after a high payoff when p=0.95. In addition, the results reflect the positive recency and inertia effects considered above.

<Insert Figure 6>

2.4 The Partial Reinforcement Extinction Effect (PREE) and reinforcement schedules

The Partial Reinforcement Extinction Effect (PREE) is one of the best-known phenomena documented in classical behavioral research. As most introductory psychology textbooks explain, the effect implies that under partial reinforcement schedules (where some responses are not reinforced), learned behavior is more robust to extinction, in comparison to continuous reinforcement (where all responses are reinforced, e.g., Atkinson et al., 1995; Baron & Kalsher, 2000; Robbins, 2001). This effect was first demonstrated in Humphreys' (1939a) examination of eye blinks in rabbits.

Humphreys (1939b) and Grant et al. (1951) show PREE in human behavior. These studies focused on promoting the behavior "predicting whether a light bulb will flash or not." Participants were presented with two light bulbs. On each trial, the right-hand bulb was blinking, and the participants had to predict whether the left bulb would blink as well.

The typical experiment included training and extinction phases and compared two conditions: Continuous reinforcement and Partial reinforcement. For example, in Grant et al.'s (1951) replication and extension of Humphreys' seminal work (1939b), the response 'Yes' (i.e., the prediction that the left light bulb would flash) was reinforced on 100% of the trials in the training phase with full reinforcement (condition full). In contrast, the response 'Yes' was only reinforced probabilistically in the partial reinforcement conditions. In the extinction phase, 'Yes' was never reinforced. Similar to Humphreys, the results demonstrated that in the extinction phase, 'Yes' responses decreased faster for the full reinforcement schedule group than for the partial reinforcement schedule groups. However, during acquisition, learning was faster as the reinforcement rate increased.

Hochman and Erev (2007) replicated the PREE using the clicking paradigm. One of their studies focused on the following problems:

Problem 30-- continuous (r=100, n=11, FB=complete, 1 point=¢0.25)

S	8 with certainty
R	9 with certainty

Problem 31 – partial (same procedure as in Problem 34)

S	8 with certainty
R	17 with probability 0.5 1 otherwise

Problem 32 – extinction (same procedure as in Problem 34)

S	8 with certainty
R	1 with certainty

The study included two phases, acquisition (the first 100 trials) and extinction (the last 100 trials). During the acquisition phase one group of participants (the continuous group) played Problem 30, and the second group (the partial group) played Problem 31. During the extinction stage, Option R was no longer attractive: Both groups were faced with Problem 32 at this phase. The participants were not informed that the experiment included two phases.

The results (c.f. Figure 7) reveal more R choices in the continuous group during the acquisition phase and the opposite pattern during the extinction phase. Thus, payoff variability slows the initial learning to prefer R during acquisition, but it also slows the extinction of this behavior.

<Insert Figure 7>

2.5 The effect of delay and melioration

Thorndike (1911) demonstrates that behavior is highly sensitive to the timing of the reinforcement. Delay of the reinforcement slows learning. This tendency implies (see Kagel, Battalio & Green, 1995) that animals behave as if they prefer a smaller immediate reward to a larger delayed reward and that this preference is not consistent with a simple discounting explanation. A clear demonstration of this pattern is provided by Green et al. (1981) in a study that used a variant of the clicking paradigm.

Each trial consisted of a 30 second choice period during which a pigeon was presented with a choice between two keys, followed by an outcome. One key led to a small reward—2 seconds of access to a grain hopper with a delay of *x* seconds —and the other to a larger reward—6 seconds of access to a grain hopper, with a delay of *x* + 4 seconds. The time variable *x* varied from 2 to 28 seconds.

The results reveal that when x is low (less than 5 seconds) each bird strongly favored the smaller more immediate outcome. The nearly exclusive preference for the smaller reward means that the pigeons failed to maximize total food intake. However, as the delay between choice and both outcomes (the time x) increased, preference reversed, with nearly every bird now choosing the larger more delayed outcome on more than 80% of the trials. That is, with longer delays the pigeons maximized total food intake.

Melioration. Herrnstein and his associates (Herrnstein, 1988; Herrnstein & Vaughan, 1980; Herrnstein & Mazor, 1987; Herrnstein & Prelec, 1991) demonstrate that in certain settings the tendency to underweight delayed payoff can lead to a robust deviation from maximization. Specifically, they show that experience can lead decision makers to behave as if they meliorate (maximize immediate payoffs[11]) rather than to maximize long term expected utilities.

For a simple demonstration of this regularity using the clicking paradigm consider the following choice task:

Problem 33 (r=200, n=20, FB= complete, 1 point=.01 Shekel)

S	1 with certainty	[S-rate: 90%]
R	+10 points with p= N(R)/(50+t) 0 otherwise	

where t is the trial number and N(R) is the number of R choices made by the participant before trial t. It is easy to see that if the experiment is long enough, Option R maximizes long term expected payoff. Yet, melioration implies S choices.

The data for Problem 33 in a 200 trial experiment reveal strong support for the melioration hypothesis. The choice rate of Option S (melioration) over the last 100 trials was 90. All 20 subjects chose S on more than 50% of the trials.

[11] Herrnstein et al. (1993) write (page 150): “Melioration can be represented analytically as a type of partial maximization in which certain indirect effects are ignored or underweighted.”

Herrnstein, Lowenstein, Prelec and Vaughan (1993) show that melioration decreases with clear information concerning the long-term effect of available choices. Thus, the evidence for melioration is best described as indication of cognitive limitations and/or insufficient exploration.

2.6 Learned helplessness

Overmier and Seligman (1967) found that dogs exposed to inescapable shocks in one situation later failed to learn to escape shock in a different situation where escape was possible. Follow up research (see review in Maier & Seligman, 1976) shows that this "learned helplessness" phenomenon is robust across species and experimental paradigms, and provides an insightful account of human depression.

The simplest explanation of learned helplessness involves the assertion that dogs can react to a shock (or to a light that signals that a shock is coming) in two ways: "Try to escape" or "Find a position that minimizes pain". Thus, experience with inescapable shocks reduces the tendency to select the try-to-escape option. Under this explanation learned helplessness is an example of melioration. The subjects fail to escape because they do not explore enough. Early experiences with unsuccessful escape attempts drive behavior even though the attempt to escape is the strategy that maximizes long-term outcome. In other words, the behavior demonstrated in the basic 2-button study of Problem 45 is an example of melioration and of learned helplessness.

2.7 Negative and positive transfer

The effect of learning in one task on the performance of a different task is referred to as transfer. Transfer is highly sensitive to the characteristics of the two tasks (see Osgood, 1949; and analysis of economic implications in Cooper & Kagel, 2003). Whereas many studies document positive transfer (improved performance on the second task), other studies document no transfer and even negative transfer. Moreover, many studies report both negative and positive transfer in the same setting. One example is provided by the transfer from Problem 30 to 32 discussed in Section 2.4: The initial transfer in this case is negative (less than 50% maximization rate in the first few transfer trials), but the long term effect is positive (higher maximization rate in Problem 32 when it is played after problem 30).

The common explanation of the existence of positive and negative transfer involves the assertion that people learn cognitive strategies (rather than situation specific actions). For example, in Problem 30 they might learn to prefer "Best reply to recent experiences" over "Alternation". This learning leads to negative transfer in the first trials of Problem 32 (S-rate below 50%), but to positive transfer after sufficient experience with Problem 32 when the recent experience implies that S leads to better outcomes.

2.8 Models of learning in dynamic settings.

Gonzalez et al. (2003) show that the main properties of decisions from experience in dynamic settings can be captured with a variant of the ACT-R model (see Anderson & Lebiere, 1998) that assumes similarity based weighting of all the relevant experiences. Under this model, decision makers are assumed to overweight a small set of experiences that occurred in situations that seem most similar to the current setting, and give lower weight to other experiences. As noted above, this idea was also found to capture behavior in static settings: It is the basis of the instance based model that won the choice prediction competition described in section 1.3.1.

Biele et al. (2009) and Hochman and Erev (2007) show that this similarity based sampling can also be used to create variants of I-SAW that capture learning in dynamic settings. This assumption is sufficient to capture adaptive behavior in restless bandit problems, and to reproduce the PREE.

Recent research shows that the current and similar results can also be captured with reinforcement learning models that include a recognition process that categorize cues into situations (see Redish et al., 2007). Gershman, Blei and Niv (2009) refine this observation and show the value of Bayesian inference within a reinforcement learning mode that assumes an unbounded number of latent causes.

2.9 The effect of additional stimuli (beyond clicking)

The current review focuses on the direct effects of obtained and forgone payoffs on choice behavior. We believe that these effects are the most important drivers of human adjustment to economic incentives. Yet, in certain settings other factors can affect this adjustment process. Two important examples are discussed below.

2.9.1 Pavlovian (classical) conditioning

The early psychological study of learning distinguishes between two classes of basic processes: instrumental and Pavlovian conditioning. Instrumental conditioning (also known as operant conditioning) describes behavior in situations in which the agent learns to prefer specific voluntary actions that affect the environment. Thus, all the studies summarized above are examples of instrumental conditioning.

The early definition of Pavlovian conditioning focuses on the association between two stimuli. For example, in each trial of Pavlov's (1927) classical study, dogs were presented with a bell few seconds before receiving food. At the beginning of the study, the bell elicited no response, and the food elicited salivation (unconditioned response, UR). Thus, the bell is called a conditioned stimulus (CS), and the food an unconditioned stimulus (US). After several trials the dogs started salivating immediately after hearing the bell.

At first glance Pavlovian conditioning does not appear to be very important in the analysis of economic behavior. However, Rescorla and Solomon (1967) show that more careful analysis can lead to different conclusions: Since Pavlovian conditioning determines emotion and related innate states, it is natural to assume that it affects the subjective interpretation of the choice environment. Rescorla and Solomon (1967, and see related ideas in Mowrer, 1947) propose a two-process model that captures this idea. Under this model, instrumental conditioning drives learning in each subjective state, but Pavlovian conditioning determines the subjective state. Since agents are likely to learn different behavior in different subjective states, Pavlovian conditioning can be highly important.

One example of the importance of the subjective states is provided by the dynamic task considered in Section 1.4.6. In this setting, distinction between the different objective states of the world enhances performance. Thus, if Pavlovian conditioning determines the agent's responsiveness to these and similar states, it determines, in part, the learning process.

It is interesting to note that Rescorla and Solomon's theory implies a very different effect of emotions than the common abstraction in economic models of emotion. Under the common abstraction (e.g., Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000), emotions like inequality aversion affect subjective utility. For example, people reject unfair offers in the Ultimatum Game because the rejection reduces disutility (negative emotion) from inequality (Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000). Rascorla and Solomon's analysis can be used to support the assumption that the main effect of emotion involves the generalization from specific past experiences. In other words, rejection of unfair offers may be a product of an emotion that directs the agent to select a behavior learned in an environment in which rejection of unfair offers is adaptive.

Another example of the economic implications of Pavlovian condition involves addiction. Smith and Tasnádi (2007) show that "harmful" addiction can be result of a mismatch between behavioral (learning) algorithms encoded in the human genome and the expanded menu of choices faced by consumers in the modern world.

2.9.2 Observational Learning

Observational learning refers to learning by observing others' decisions and payoffs. A number of animal studies support observational learning. Terkel (1996) shows that young rats learn to skin pine cones by observing their mothers. John et al. (1969) show that cats can learn tasks by observing the performance of an animal already trained in that particular task.

Miller and Dollard (1941) argued that observational learning is no different than simple reinforcement learning in that observational learning involves situations where the stimulus is the behavior of another person and the payoff maximizing behavior happens to be a similar behavior. In one of their experiments, first grade children were paired, with one in the role of "leader" and the other in the role of "follower." In each trial, the children sequentially entered a room with two boxes. In one of the boxes, there was candy. The leader first chose a box and obtained any candy that was in there. The follower observed which box the leader chose but not the outcome of that choice. Next, the contents of the boxes were emptied and candy was again placed in one box. The placement of the candy was manipulated in two treatments. In one treatment, the candy was placed in the box previously selected by the leader. In the other treatment, candy was placed in the box not chosen by the leader. The follower then entered the room and chose a box. After a few trials, children in the first group always copied the response of the leader and children in the second group made the opposite response.

Bandura (1965) argued that the payoff received by the observed person should matter in the decision of whether to imitate that person. In Bandura (1965), a group of four-year-old children watched a short film on a TV screen in which an adult exhibited aggressive behavior towards an inflated 'bobo doll'. The children then saw the aggressor being reinforced by another adult. In one treatment, the aggressor was praised and given soda and snacks. In a different treatment, the adult was scolded, spanked and warned not to do it again. The children were then left in a room with the doll along with other toys. The imitation and aggression were more pronounced when the adult was observed by the children receiving a reward for his actions and less pronounced when the adult was punished.

Merlo and Schotter (2003) raise the prospect that in some settings observational learners may learn better than subjects engaged in the task. In their experiments, subjects chose a number between 0 and 100. The higher the number chosen, the higher the cost incurred by the subject and the higher the probability of winning the high prize, resulting in an interior optimal choice of 37. Subjects in the baseline experiment repeated the decision task 75 times and were paid a small amount after each trial. As each subject performed the experiment another subject watched over his or her shoulder. In the end of the 75 trials, the observers as well as the active subjects were both given one round of the task with high stakes. The median choice in the high stakes decisions by the observers was 37 (the optimal choice), whereas the median choice by the subjects who engaged in the small stakes task 75 times was 50. Merlo and Schotter (2003) offered this as evidence that the observers learned more effectively than the subjects engaged in the task.

Anderson and Holt (1997) studied an interesting situation in which equal weighting of personal information and observation learning (the implied information obtained by other) leads to information cascade (that is, it stops the accumulation of knowledge). Their results show a lower rate of information cascade than predicted under the rationality assumption. This pattern can be explained by the assumption that people overweight their personal information. Clear support for this assumption is provided by Simonsohn et al. (2008). The participants in their studies received feedback concerning their payoffs (personal experience) and the payoffs of other agents. The results show that the effect of the personal experience was much larger than the effect of the experiences of others. Alos-Ferrer and Schlag (2009) reviews theoretical research that focuses on the value of imitation as a learning strategy. Their analysis demonstrates that payoff sensitivity of the imitation rule facilitate the social value of imitation. Efficiency can increase by a tendency to rely on personal information if the advantage of imitation is small.

3. Social interactions and learning in games

It is constructive to distinguish between two main effects of the social environment on choice behavior. First, the social environment can affect the strategies considered by the decision makers, and/or the utility from the obtained payoffs. For example, it can lead the decision makers to consider strategies that facilitate reciprocation, increase fairness, and/or build trust. The second effect is indirect: the social interaction affects the obtained payoffs, and these payoffs shape behavior.

Most previous experimental studies of social interactions (games) focus on the direct "reciprocation-related" effects of the social environment (see Cooper & Kagel, 2012). The current review tries to complement this research by focusing on the indirect effect of the social environment. It builds on the observation (Roth & Erev, 1995, Erev & Roth, 1998) that there is wide set of situations in which the understanding of the obtained payoffs is sufficient to predict the outcome of social interactions. The effect of experience in this space of social situations is similar to the effect of experience in individual choice tasks, and it can be approximated with simple reinforcement learning models like I-SAW. One class of social interactions that belongs to this "basic shaping" space is the class of market entry games examined in the choice prediction competition described in Section 1.3.2. The best prediction of the outcome of this class of social interactions was provided by models that were developed to capture the basic properties of learning described in Section 1.1.

The main goal of the current section is to clarify the boundaries of the basic shaping space. Specifically, it examines the conditions under which the outcome of complex social interactions can be reliably predicted based on simple models that assume learning among the possible alternatives. In addition, it tries to shed light on the assumptions that has to be added to the basic models in order to capture behavior beyond this basic space.

Section 3.1 considers studies of learning in games under limited prior information. The results reveal examples of "emerged sophistication" that can be predicted with I-SAW and similar models.

Section 3.2 reviews studies of learning in 2-person constant sum games with unique mixed strategy equilibrium. The results reveal that prior information can affect the sequential dependencies in the data, but has little effect on the aggregated choice rates.

Section 3.3 summarizes studies of cooperation and coordination. The results reveal that under certain conditions players can learn to maximize efficiency by reciprocating and coordinating. In addition, the results suggest that this "learning to reciprocate" phenomenon is rather delicate. It is likely to emergence only when all the following six conditions are met: (1) the agents receive reliable and complete description of the incentive structure, (2) the benefit from reciprocation is large, (3) the number of interacting agents is small (four can be is too large), (4) the noise level is low, (5) the interaction is expected to continue with high probability, and (6) the framing of the task clarifies the value of reciprocation. These results can be captured with the assertion that players consider "try to reciprocate" cognitive strategies. Yet, the set of situations under which these strategies are learnt are not large.

Section 3.4 discusses studies that explore the role of fairness. The results show that in certain settings people behave as if they try to maximize fairness. However, in other settings they choose actions that reduce equality even when this action impairs expected return. This pattern can be captured as another indication of considering, but not always using "try to reciprocate" cognitive strategies.

Section 3.5 summarizes the main results and discusses alternative explanations and several open questions.

3.1 Social interactions given limited prior information

3.1.1 The group size effect in mutual fate control games.

Sidowski et al. (1956; and see Colman, 2005; Colman et al., 2010; Delepoulle, Preux, & Darcheville, 2000, 2001; Mitropoulos, 2001, 2003) studied a minimalistic 2-person social situation in which the players can help each other, but cannot affect their own payoff directly. The left-hand side of Figure 8 presents a member of this class of games that was studied in a 200-trial experiment by Colman et al. (2010).

<Insert Figure 8>

Notice that traditional game theoretic analysis does not have clear predictions for the current game. For example, all four cells are "weak Nash equilibrium" points in a one-shot play of the game.[12] The participants in the typical experimental study of this class of games do not receive any information concerning the payoff rule, and interact repeatedly in fixed pairs. The results show that most pairs slowly learn to coordinate on the efficient outcome (the "1,1" cell). The proportion of efficient coordination after 100 trials is close to 70%.

Thibaut and Kelley (1959) show that this learning process can be a product of a *win–stay- lose–shift* (WSLS) decision rule. This rule implies a repetition of the last choice after high payoff, and a change after a low payoff.

Colman et al. (2010) examine the effect of the number of interacting players in a multiplayer generalization of the mutual fate game. In the generalized game the players are placed in a ring, and each player has a predecessor on her left and a successor on her right. The payoff of each player is determined by her predecessor (the player receives 1 only if her predecessor chose C), and the action of each player determines the payoff of her successor.

[12] Nash equilibrium is defined as a prediction of the strategies of the different players from which no player has an incentive to deviate. That is, if a player believes that her opponent will follow a particular Nash prediction, she cannot benefit by deviating from this prediction. An equilibrium is "weak" if a deviation does not change the deviator's payoff.

The WSLC rule implies efficient coordination in multiplayer mutual fate games when the number of interacting agents is even (see Colman et al., 1990). Colman et al.'s (2010) experimental results, presented in Figure 8, do not support this prediction. Rather, they reflect a large qualitative difference between the basic N=2 condition, and the N > 2 conditions. The players learned to coordinate when N=2, but not when N>2. A similar group size effect was documented by Feltovich, Iwasaki and Oda (2007) in a study of a Stag Hunt coordination game.

Colman et al. (2010) show that this group size effect can be captured with models that imply a stochastic WSLC decision rule, and note that this class of models includes the leading models of decisions from experience in individual choice tasks (like I-SAW) presented in Section 1.

3.1.2 Quick and slow learning in market entry games.

Erev and Rapoport (1998) document surprisingly fast convergence to Nash equilibrium in 12-person market entry games that were played without prior information of the payoff rules. In each trial of one of these games, participants chose between "entering" and "staying out" of the market. Staying out paid a sure payoff of 1. The payoff for entering was 1 + 2(4 – E), were E is the total number of entrants.

This game has multiple pure strategy equilibria, and one symmetric mixed-strategy equilibrium. The average number of entrants, at these equilibria, is between 3 and 4. The observed number of entrants in trials 15 to 20 (the last block) was 4.1, and the mean obtained payoff was between the expected payoff under the mixed and the pure equilibrium points.

At first glance, this emerged coordination appears to contradict the low predictive value of the equilibrium predictions in market entry game competition described in Section 1.3 (the ENO of the equilibrium prediction in this study was below 1). However, there is a simple explanation to the difference between the two studies. Erev and Rapoport show that their results can be predicted by reinforcement learning models (I-SAW is one of the models that can capture these results). These models predicts quick convergence to equilibrium when the payoff variability is low (as in Erev & Rapoport, 1998), and robust deviations from equilibrium when the payoff variability is high (as in some of the games in the market entry game competition).

3.2. Learning in constant-sum games with unique mixed strategy equilibrium

A two-person constant-sum game is a simplified social interaction that captures pure conflict: The sum of the payoffs of the two players is fixed, and the players cannot reciprocate. The game presented in Figure 9 is an example of a constant sum game with unique mixed strategy equilibrium. In this equilibrium Player 1 selects A1 with probability p = 3/8 and Player 2 selects A2 with probability 7/8. Under this mixed strategy, Player 2 is expected to receive the same payoff from A2 (EV = 0.7(3/8) + 0.6(5/8)) and from B2 (EV= 0.2(3/8) + 0.9(5/8)). Thus, Player 2 is not motivated to deviate from his predicted behavior. Similar logic holds for Player 1.

<Insert Figure 9 Here>

3.2.1. Learning away and limited effect of prior information**.**

Suppes and Atkinson (1960) examined Figure 9's game in a 210-trial experiment. The participants were run in fixed pairs: One participant was assigned to be Player 1, and the second participant was assigned to be Player 2. The payoffs are the winning probabilities. For example, if Player 1 selects A1 and Player 2 selects A2, then Player 1 wins with probability 0.7 and Player 2 wins with probability 0.3.

Two information conditions were compared. The payoff matrix was known to the participants in Condition Known, and unknown in Condition Unknown. The feedback after each trial was limited, in both conditions, to the realized outcome (Win or Loss).

The results, presented in the left-hand columns of Figure 9, reveal a very small difference between the two conditions. The following observations summarize the results under both conditions: (1) The initial choice rates are close to 50%. (2) With experience Player 2 increases the tendency to Select A2. That is, Player 2 moves toward the equilibrium prediction. However, this movement is very slow. Even after 200 trials the proportion of A2 choices is closer to 50% than to the equilibrium prediction (7/8 = 87.5%). (3) Player 1 moves away from the equilibrium prediction: The observed proportion of A1 choices was above 60% (in equilibrium Player 1 is expected to select A1 in only 37.5% of the trials).

Follow-up research shows the robustness of the pattern documented by Suppes and Atkinson (1960). Slow learning, and learning away by one of the players are quite common in constant sum games with unique mixed strategy equilibria. Ochs (1995) shows that a similar pattern can be observed in non-constant sum games that are played "against a population." (The experiment was run in cohorts of 8 or more subjects in each role. In each trial all the participants in the role of Player 1 played against all the participants in the role of Player 2).

Erev and Roth (1998, and see a clarification in Sarin & Vahid, 1999) demonstrate that learning away by one player is predicted by simple models that assume exploitation (selection of the alternative that led to the best outcome in the past), and exploration/error (random choice). I-SAW is an example of this class of models. The right-hand column in Figure 9 shows the predictions of I-SAW (with the parameters estimated above) for the current game.

Additional indications of the robustness of the current results are presented in Table 4. This table summarizes the results of experimental studies of three randomly selected constant sum games. The games were run under two conditions. In Condition Minimal (see Erev et al., 2002), the participants did not receive a description of the payoff matrix, and the feedback was limited to the obtained payoff. In Condition Complete (see Erev et al., 2007) the participants received a complete description of the payoff matrix and complete feedback. Each game was run for 500 trials under fixed matching. The results show relatively small difference between the two information conditions (the correlation is 0.9), and learning away by one of the player in about half of the games. In addition, the results replicate previous studies (e.g., O'Neill, 1987) that demonstrate relatively good match between the equilibrium predictions and the observed choice rate when the equilibrium predictions are between .4 and .6.

<Insert Table 4>

The right-hand column in Table 4 presents the predictions of I-SAW (with the simplification assumptions and parameters used in Section1) for the complete feedback condition. The MSD score is 0.0047 and the correlation is 0.93. This fit is better than the fit of the best model proposed in the original paper.

3.2.2 Sequential dependencies.

Under one interpretation of the results presented above, they imply convergence to equilibrium when these predictions are close to uniform choice proportions. Several studies have test and reject this interpretation. Brown and Rosenthal (1990) reanalyzed O'Neill's (1987) results and found strong evidence of serial correlation in players' choices that contradict the equilibrium prediction (that imply no sequential correlations). The typical subjects exhibit over-alternation. A similar over-alternation bias was also documented by Rapoport and Budescu (1997) in a 2x2 game. Shachat (2002) shows that this deviation from the equilibrium emerges even if players are allowed to use a randomization device.

Additional research suggests that the exact nature of the sequential dependencies in constant sum games is situation specific. For example, evaluation of the sequential dependencies in the 10 constant sum games presented in Table 4 reveals that most subjects exhibit the opposite bias: Strong inertia (see Slonim, Erev & Roth, 2007). Under one explanation of this pattern, over-alternation emerges when the players are informed that they select between objectively identical alternatives.

3.2.3 Modeling robust choice rates and slippery sequential dependencies.

The constant-sum results presented above appear to reflect an interesting inconsistency: Section 3.2.1 suggests that the aggregated choice rates can be predicted with the assumption that behavior in different constant sum games is driven by a general learning model like I-SAW, and Section 3.2.2 suggests situation specific sequential dependencies. One resolution of this apparent inconsistency is based on the assumption that the different sequential dependency patterns are reflections of different situation- and person-specific exploration patterns that have limited effect on the aggregate choice rate (see a similar idea in Rapoport et al., 1997). This resolution can be naturally abstracted in a variant of I-SAW that allows for the possibility that during exploration the agents tend to alternate between alternatives that are known to be similar.

3.3 Cooperation, coordination, and reciprocation.

Rapoport, Guyer and Gordon (1976) show that under certain condition people can learn to cooperate in public good games, and can learn to achieve efficient coordination. A clear demonstration of the emergence of cooperation is provided by the study of the Prisoner's dilemma game presented in Figure 10 (Game PD1).

Each player in this 2-person normal-form game has to select between Cooperation (C) and Defection (D). When the game is played once, D is a dominant strategy (and the unique Nash equilibrium of the game). That is, each player earns more from selecting D than from C, independently of the choice of the other player. Yet, both players earn less when both select D (payoff of -1) than when they select C (payoff of 1).

In one of the experimental conditions, the participants played Game PD1 for 300 trials against the same opponent (fixed matching) with immediate feedback after each trial (and without knowing how many trials would be played). The results (c.f. upper panel in Figure 10) show an increase in cooperation with experience. The cooperation rate in the last block was higher than 60%.

<Insert Figure 10 Here>

A clear indication of the emergence of coordination is provided by Rapoport, Guyer and Gordon's (1976) study of following chicken game:

Game: Chicken 1	Swerve	Drive
Swerve	1,1	-1,10
Drive	10,-1	-10,-10

Notice that the game has two pure strategy equilibria, and one mixed strategy equilibrium. The pure strategy equilibria (Swerve, Drive and Drive, Swerve) are efficient (joint payoffs of 9) but unfair (one player wins 10 and the other loses 1). At the symmetric mixed strategy equilibrium, both players Drive with probability 1/2 and the expected payoff is 0. The results reveal that the participants were able to achieve a high level of cooperation. The efficient outcome (joint payoff of 9) was obtained in 84% of the trials. In addition, the results reveal a high level of fairness. The difference between the proportions of driving choices was lower than 7% for all 10 pairs.

Alternation behavior (that facilitates efficiency and fairness) was also shown by Arifovic et al. (2006). They show that subjects playing repeated Battle of the Sexes, where there are two pure strategy Nash equilibrium outcomes each favoring one player, often fall into a stable pattern of alternation between the two pure-strategy Nash equilibria. The data provided on the website accompanying the article shows that, out of 16 subjects matched in 8 fixed pairs, 56% individually alternated beginning in period 2. This is the proportion of subjects who chose a different action in period 2 than they chose in period 1. By period 3, this proportion rose to 88% and by period 6, it reached 94%, which is all but one of the 16 subjects.

The emergence of cooperation and alternation-based-coordination described above cannot be captured with basic reinforcement learning models like I-SAW. In the current context, human agents exhibit higher "social intelligence and/or sensitivity" than assumed by the basic learning models. In order to clarify the implications of this observation, the following review studies that highlight its boundaries.

The effect of the relative benefit from reciprocation. Rapoport and Chammah (1965) compare Game PD1 with other six prisoner dilemma games (same ordering of the payoffs). Their results reveal high sensitivity to the relative benefit from cooperation. For example, when the payoff on the cost of unilateral cooperation was increased from 10 to 50, and the benefit from unilateral defection was increased from 10 to 50, the cooperation rate decreased to 27%.

Size matters. The increase in cooperation with experience, discussed above, tends to weaken and even disappear as the number of interacting subjects gets large. Recent studies (e.g., Isaac and Walker 1988, Andreoni & Miller, 1993; Daniely, 2000, Huck, Normann & Oechssler, 2003; Bereby-Meyer & Roth, 2006, Apesteguia, 2006) show that the likelihood of "learning to cooperate" is highly sensitive to the number of interacting agents. An increase in the number of interacting agents tends to increase the tendency to select the dominant strategy. A similar pattern was documented in the study of coordination games (Van Huyck et al., 1990; Bornstein, Budescu and Zamir, 1997).

For example, Daniely (2000) compared two versions of Rapoport and Chammah's prisoner dilemma experiment (using Game PD1). The first was a computerized replication of the original study. The participants were run in cohorts of four that were divided into two pairs. Each pair interacted 300 times. The results of this condition were very similar to the original results. The proportion of cooperation in the last block of 50 trials was 80%. The second condition (c.f. Figure 10) was identical to the first with the exception that the four participants in each cohort were randomly re-matched after each trial. This change had a dramatic effect on the results. The proportion of cooperation in the last block of 50 trials dropped to 10%.

Apesteguia (2006) examined a 6-person public good game with and without description of the payoff rule. The results reveal very similar pattern in the two conditions. Another source of support to the suggestion that reciprocation is highly sensitive to the increase from 2 to 4 players is provided by Isaac and Walker (1988). They examined public good games (that can be described as generalized multi-player prisoner's dilemma games). Their results showed a low cooperation rate in 4 player groups, and similar rates with 7 agents (when the cost of cooperation is fixed).

The role of framing. In addition to the two conditions described above, Daniely (2000) studied the effect of framing. She tried to replicate the fixed matching study of Game PD1 with the framing of the task as a transportation problem. Each player controlled a simulated car that approached a traffic light, and had to decide between "staying in his lane" and "changing lane." The decision to change lane increased the player's payoff, and decreased the payoff of the other player. The exact payoff rule was determined by Game PD1 with changing imply D, and staying implies C. As in the original study, the participant received a complete description of the payoff rule, the feedback after each trial was complete. The only change between the studies was the addition the transportation cover story. The results reveal that this addition eliminated the increase in cooperation. The observed cooperation rate in the last block of 50 trials was only 18%. Additional indications for the robustness of framing effect in the context of social interactions are presented by Rottenstreich (1995).

The shadow of the future. Selten and Stoecker (1986) studied behavior in a sequence of prisoner's dilemma games. Each player played 25 supergames, where each supergame consisted of 10 periods play of Game PD2 (first panel in Table 5). Following each supergame, each player was re-matched to a new opponent. The typical outcome was initial periods of mutual cooperation, followed by an initial defection, followed by non-cooperation in the remaining periods. That is, the shadow of the future, the understanding that the game is about to end, decrease cooperation. The first period of defection occurs earlier and earlier in subsequent supergames. Selten and Stoecker note that this learning pattern can be captured with a simple direction learning model.

<Insert Table 5>

Andreoni and Miller (1993) studied Game PD3 (second panel in Table 5) using the Selten and Stoeker sequence of prisoner's dilemma design. Their results replicated the decrease in cooperation within supergames documented by Selten and Stoeker, but observed an increase in cooperation with experience over supergames. The difference between the two studies can be attributed to the weaker temptation to defect in Andreoni and Miller's matrix. This interpretation of the results is supported by Dal Bó and Fréchette (2007).

Noise matters. Bereby-Meyer and Roth (2006) examined the effect of payoff variability on choice behavior in a prisoner's dilemma game under Selten and Stoeker's supergame paradigm and under random matching. They focused on Game PD4 (lower panel in Table 5). In the stochastic condition, the matrix entries represented probability of winning $1. In the deterministic condition, the entries represented payoffs in cents. The results reveal an interesting interaction. Payoff variability increased cooperation given random matching, but impaired cooperation under repeated play.

The effect of prior information. Coordination and reciprocation becomes very difficult when the agents do not know the incentive structure. As noted in Section 3.1 when the information is limited, coordination is difficult even in a common interest game.

3.3.1 Alternative abstractions: Social utilities and cognitive strategies

Previous reserach highlights the value of two main approaches to capture the effect of experience on cooperation and coordination. One approach is based on the importance of social utilities. For example, an increase with reciprocation can be captured with the assumption that successul reciprocation is reinforcing (see Macy & Flache, 2002; Vega-Redondo, 1997; Juvina, Lebiere, Martin & Gonzalez, 2012). One recent demonstration of the potential value of generality of this approach is the observation that people behave as if they find the act of following advices reinforcing (see Biele et al., 2009).

A second approach involves the assertion, discussed above, that people learn among a subset of repeated game strategies. For example, Erev and Roth (2002) assume that the player considers a “reciprocation” strategy that implies an effort to reach the most efficient outcome (and punishing opponents that deviate from this play). When this strategy leads to good outcomes, players learn to select it. In another model (Hanaki et al., 2005), the players are assumed to consider strategies that can be represented by automata having no more than two states. Analysis of this model shows that it can capture the emergence of reciprocation considered above. Alternative abstraction of the cognitive strategies idea involve a distinguiction between learning and teaching (see Camerer, Ho & Chong, 2002; Ehrblatt, Hyndman, Ozbay, & Schotter, 2006). Cooperation emerges under these models when sophisticated players (agents that use sophisticated strategies) are able to teach their opponents that cooperation in beneficial.

3.4. Fairness and inequity aversion.

Studies of decisions from description demonstrate that in certain cases people try to avoid inequity (increase fairness) even when this effort decreases their payoff (see (review in Cooper & Kagel, 2012). Evaluation of the effect of the effect of inequity on learning reveals mixed results: Some studies show strong evidence for inequity aversion, but some studies suggest inequity seeking.

One demonstration of the effect of equity on learning is provided by Rapoport et al. study of the prisoner dilemma game described in Figure 10. Their results show almost perfect correlation between the payoffs of the two agents in each pair.

Another indication for inequity aversion is provided by studies of repeated ultimatum games (Guth et al., 1982). In the basic version of this game one player-- the proposer-- proposes a division of a pie (e.g., $10 in the experiment considered below) between herself and a second player. In the second stage the second player-- the responder-- can accept or reject the proposal. If she accepts each player gets the proposed share. If she rejects, both get nothing. The game-theoretic solution (subgame perfect equilibrium) states that the proposer should offer the smallest possible amount to the receiver, and the receiver should accept it. Abbink, Bolton, Sadrieh and Tang (2001) examined a variant of this game in which the proposer's payoff, in the case of a rejection, are either 0 (as in the original game) or 10. Only the responders were informed of the proposer rejection payoff. The results reveal that the responders were three times more likely to reject the unequal split when doing so enhanced equity (both players got 0) than when it reduced equity (when the rejection payoff to the proposer was of 10).

Indication for inequity seeking is provided by study of betting games (Sonsino et al., 2002). The results reveal that participants tend to bet even after 250 trials in which betting decreases equity, and impairs expected return.

3.5. Subjective summary and alternative approaches

The current review of the study of learning in social interactions supports three suggestions. First, the main difference between learning in games and learning in individual choice tasks involves the emergence reciprocation: In certain situations agents learn to increase their payoff by cooperating and coordinating. Second, the emergence of reciprocation can be captured with the assertion that the agents consider "try to reciprocate" cognitive strategies. Strategies of this type drive choice behavior when they are reinforced. Finally, the results suggests that there are many situations in which the effort to reciprocate has little effect on choice behavior. In these cases the effect of the incentive structure can be predicted with the basic learning models presented in Section 1.

It is important to recall that the current summary of the results is based on one research method. Our analysis starts with I-SAW as a benchmark, and used assumptions concerning cognitive strategies to explain the observed deviations from the predictions of this benchmark. It is possible that different research methods will lead to different and more insightful conclusions. We chose to conclude the current section with a discussion of the potential of three of the methods that were not used here.

3.5.1 More realistic psychological assumptions

Marchiori and Warglien (2008) highlight and explore the value of simple artificial neural networks as models of learning in games with unique mixed strategy equilibria. The basic model they considered assumes the most elementary learning neural network architectures: the one-layered analog perceptron (Hopfield, 1987). This model learns by adapting the connection between the possible payoff and the action in the ex post best reply direction. The second model was a variant of the basic model that adds the assumption that the magnitude of the adaptation increases with regret.

The predictions of this model for the 2x2 constant sum game presented in Table 4 are similar to the predictions of I-SAW. Thus, it is possible that Marchiori and Warglien approach can be used to improve our understanding the brain computations that give rise to the basic properties of learning processes.

3.5.2 More sophisticated econometrics

The discussion of learning models presented above uses simple computer simulations in order to derive predictions and evaluate different models. This analysis has two important shortcomings. First, it is inefficient: It uses only small part of the data in order to estimate the model. For examples, most analyses focus on the aggregate choice rates, and ignore the effect of many details of the observed experiences. Second, it is subjective: We did not use an objective parameter search algorithm. Rather, the parameters were estimated with a manual greed search procedure.

It is natural to assume that this analysis can be improved with the usage of more efficient and objective econometric analyses. One demonstration of the potential of sophisticated econometric analysis in the current setting is presented by Camerer and Ho (1998). Their analysis focuses on the relative importance of reinforcement and belief learning. To evaluate this issue they developed a model, referred to as Experience Weighted Attraction (EWA), which parametrically nests variants of reinforcement learning and belief learning and allows for estimation of the weight given to the different processes. Then they used efficient and objective econometric methods to estimate the parameters of this model. Their analysis suggests that the weight tend to be between 0 and 1, and that the EWA significantly outperforms the two basic models. In addition, their analysis suggests that allowing game-specific parameters significantly improves the fit. Thus, it is possible, using EWA, to estimate the factors that drive learning in a particular game. This observation has been effectively used by many researchers to shed light on learning processes (e.g., Anderson & Camerer, 2000; Arifovic & Ledyard, 2004; Amaldoss & Jain, 2005; Rapoport & Amaldoss, 2004).

Recent research shows, however, that econometric analysis of learning models should be viewed with some caution. Feltovich (2000) show the ranking of different models can be highly sensitive to the selected statistic. He generated predictions from two models (under several parameterizations) using two different approach. Under one approach, the predictions were made in each period based on the entire history of play of the individual up to that period (as in Camerer and Ho, 1999). In another, the predictions were made for the entire path of the game based only on game payoffs and initial conditions (as in Roth and Erev, 1995). The results reveal serious inconsistencies in the comparative rankings of the models between the results of the two approaches.

Salmon (2001) argued that human decision makers are not likely to use the precise specification as the econometric model being estimated. Therefore, he argued, a desirable characteristic of a model is that it be able to identify characteristics of the underlying decision making process, even if that process does not exactly correspond to the econometric model being estimated. As in Feltovich, Salmon takes the view that the definition of a model includes the parameter values affixed to it. Salmon simulated data for constant sum normal form games, from EWA, with different sets of parameters values, representing Cournot best response as represented under EWA, fictitious play as represented under EWA, and reinforcement learning as represented under EWA, as well as from a straight fictitious play and from a population mix of two pure subpopulations. He then estimated the models of Mookherjee and Sopher (1994, 1997), which have both reinforcement learning and belief learning variants, and Cheung and Friedman, which is only specified for belief learning. He finds that the models have mixed success in separating out belief learning populations from reinforcement learning populations, with special difficulty in the latter. Most surprising is the finding that EWA only had correct identification of populations (that were originally generated by EWA) in only 50% of the cases. Salmon notes that this is because the reinforcement learning and belief learning populations generate very similar patterns of behavior, a finding echoed by Feltovich (2000). These similar patterns impair accurate estimation of the data-generating process.

As in Salmon (2001), Wilcox (2006) uses simulations to see if models (EWA in particular) could capture properties of behavior under model mispecification. Wilcox (2006) shows that the estimate of the "attention to foregone" parameter of EWA is highly sensitive to heterogeneity. In a careful study, Wilcox (2006) generated simulated data for a matching pennies game and stag hunt games coming from an EWA population with zero, low or high heterogeneity on all parameters except the "attention to foregone" parameter. He then estimated the EWA on the data using pooled estimates (assuming no heterogeneity). He found that even with low heterogeneity, the estimate of the "attention to foregone" parameter is dramatically downward-biased. With high heterogeneity, the bias is so large that the estimated value of "attention to foregone" is alarmingly close to zero, even when the true value is 1. Therefore, without accounting for heterogeneity, one might erroneously conclude that subjects do not pay attention to foregone payoffs to the extent they actually do. Likewise, the estimated values of other important parameters may be biased and misinterpreted.

3.5.3 The long term and intermediate term

The most elegant analysis of the effect of learning on economic behavior involves the analytical derivation of the long-term properties of simple adaptive models (see e.g., Milgrom and Roberts, 1990; Kalai & Lehrer, 1993; Kandori, Mailath & Rob, 1993; Fudenberg & Levine, 1998 Hart & Mas Collel, 2001).

This line of research results in two main insights. The first insight is that under standard assumptions adaptive models converge to some Nash equilibrium (Kalai and Lehrer, 1993). This link between adaptive convergence and equilibrium has been carried father to where adaptive models have become an integral tool of game theoretical predictions. For example, in games with multiple equilbria, evolutionary adaptive dynamics can serve as both an equilibrium selection and an equilibrium refinement tool (Kandori, Mailath and Rob, 1993). As another example, in finite strategy supermodular games with multiple equilibria, the convergence of any adaptive process has been shown to be bounded by and linked to the set of Nash equilibria (Milgrom and Roberts, 1990).

A second and equally important insight is that under simple assumptions (e.g., infrequent switching), adaptive models are in the long run approximately optimal from the decision maker's point of view in that they ensure that the decision maker's payoff is nearly the best possible payoff against the historical frequency of play by his opponents. Fudebnberg and Levine (1998) show this property for smooth fictitious play, where the probability of each action is an exponential function of that action's utility against the historical frequency of the opponents' play. They also discuss other models that have this property. Hart and Mas Collel (2001) generalize this to broad class of adaptive models of which fictitious play is one case.

Roth and Erev (1995) clarify one limitation of the focus on "data free" long term predictions. They show that small details of learning models that have limited effect on the intermediate term predictions (the predictions that can be validated in experiments lasting from two trials to thousands of trials) can drive the long term predictions (behavior following many millions of trials). For example, the assumed discounting rate in the model reinforcement learning model considered by Roth and Erev has no effect on the predicted behavior in the ultimatum game after 10,000 trials, but it determines if behavior will converge to the subgame equilibrium after millions of trials.

Recent research on the convergence properties of learning models addresses this critique with a focus on models that converge to the observed experimental results. One elegant example is provided by Quantal Response Equilibrium (McKelvey & Palfrey, 1995). This model that assumes consistent exploration (or a noisy response rule) and sensitivity to exploration by others at equilibrium, provides an insightful summary of behavior for a wide set of situations (see e.g., Anderson, Goeree & Holt, 2001; Goeree, Holt & Palfrey, 2002).

Other elegant examples of the value of descriptively motivated equilibrium models are offered by Impulse Balance Equilibrium (see Ockenfels & Selten, 2005; Selten & Chmura, 2005), and by Sampling Equilibrium (Osborne & Rubinstein, 1998) that approximates the intermediate term predictions of I-SAW.

4. Applications and the Economics of Small Decisions

The experimental studies reviewed above focus on small decisions: The stakes in the typical experimental task were small, and the participants did not invest very much time and/or effort in each choice. Nevertheless, we believe that the behavioral regularities documented in this research can be of high practical value. Our belief is based on three sets of observations. First, many important economic phenomena are the direct product of small decisions. For example, small decisions by drivers (e.g., the decisions between the gas and the break pedal) affect traffic accidents, traffic jams, and pollution. Similarly, small clicking decisions by internet users determine the future of newspapers, and of the music industry.

Second, in many settings high stakes decision problems are shaped by small decisions. For example, consider the high stake decision among different job offers. In many cases this big decision problem is affected by earlier small decisions. The job offers available to a specific college graduate are likely to depend on small decisions that she has made as a child and as a student. Small decisions that lead to high grades, and good connections tend to improve the job offers.

A third set of observations come from studies that directly examine the practical implications of the learning phenomena presented above. Some of these studies are reviewed belowwe have discussed.

4.1 Gentle COP 1: The enforcement of safety rules.

Erev & Rodensky (2004; Schurr, Erev & Rodensky, 2012; and see related idea in Zohar, 1980) note that the research reviewed above has five implications for the design of safe working environments. First, the results suggest that rule enforcement is necessary even when safe behavior (e.g., the use of safety equipment) is the rational course of action. The explanation of the relevant risks might not be enough. When workers make decisions from experience they are likely to underweight the low-probability-high-hazard event and behave as if they believe "it won't happen to me."

Two additional implications concern the effectiveness of rule enforcement systems in which a small proportion of violations are severely punished (see Becker, 1968). The current review implies that systems of this type are likely to be effective in the context of decisions from description, but less effective or ineffective in the context of decisions from experience. When decisions are made from experience, low probability punishments are likely to be underweighted. A related implication comes from studies of the importance of fairness considerations in social interaction, as in the studies of the ultimatum game discussed earlier. This research suggests that the implementation of "low probability heavy punishments" may be very difficult if subjects of the recipient role can affect the enforcers (proposer role). Under the assumption that punishment may seem unfair (because only some violators are punished), some recipients are likely to retaliate even if retaliation is costly to them. Thus, enforcers (proposers) might learn to avoid using these punishments.

A fourth implication is optimistic. It implies that the fact that workers take unnecessary risks and behave as if they ignore safety rules does not imply that they will object to attempts to enforce these rules. Indeed, the observation that low probability events are over-weighted in decisions from description implies that when workers are explicitly asked to consider the safety issue they will agree that they want to behave safely, and will be happy to see that the management designs a rule enforcement system to help them achieve this goal.

Finally, the arguments presented above suggest that behavior is much more sensitive to the probability than to the magnitude of the punishment. Thus, a gentle Continuous Punishment ("gentle COP") policy that implies low punishments with high probability can be very effective (as long the fine is larger than the benefit from violations of the rule).

Erev and Rodensky (2004, and see Erev, 2007) applied this “gentle COP” method in twelve Israeli factories. The basic idea was the design of a mechanism by which supervisors will be encouraged to approach each worker who violates the safety rule and remind him that this behavior might result in injury, and will be recorded (if repeated). The official role of these “violations records” was to allow the management to positively reinforce workers who observe the safety rule by giving these workers a higher probability of winning a lottery. Baseline data were collected about two months prior to intervention. The data included objective measures of the workers’ safety behaviors (c.f. Figure 15). The intervention started with a formal presentation of the new policy to all the workers. Figure 15 presents measures of safety related behavior before and after the presentation in one of the departments in one of the twelve factories. The data were collected by the research team, and were independent of the supervisors’ comments and records.

<Insert Figure 15>

As demonstrated in Figure 15, the intervention had a large and immediate effect. A similar pattern was observed in all twelve factories. The rate of safe behavior increased to 90% immediately after the beginning of the intervention. More interesting is the observation that the effect of the intervention did not diminish with time. The rate of safe behavior increased or stayed high during the two years since the beginning of the intervention. Given the success of the intervention, and its relatively low cost, the factories have decided to maintain the experimental policy after the experiment.

4.2 Gentle COP 2: Cheating in exams

One of the likely contributors to the long term success of the gentle COP procedure, described above, is the observation that multiple equilibria are common in rule enforcement problems, including tax compliance (Alm & McKee, 2004) and corruption (Tirole, 1996; Waller, Verdier & Gardner, 2002). In one equilibrium, obeying the rules is the norm, and the enforcers can easily detect and punish deviations if they occur. Thus, no one is motivated to start violating the rule. In a second equilibrium, violation is the norm, and the enforcers are unable to cope with the frequent violations. The possibility of two extreme equilibria and the hypothesis that small decisions are made based on experience in similar situations implies that the effectiveness of different rule enforcement policies is likely to be particularly sensitive to the initial actions. Wise allocation of initial resources can lead to a convergence to the "good" equilibrium in which observing the rule is the norm.

Erev, Ingram, Raz and Shany (2010) applied this reasoning to cheating on college exams. Their analysis suggests that gentle COP policies can be used to move behavior to the "good" equilibrium. To evaluate this hypothesis they run an experiment during final semester exams of undergraduate courses at the Technion. Traditionally, instructions for exam proctors at the Technion included the following points:

(1) The student's ID should be collected at the beginning of the exam,

(2) A map of students' seating should be prepared.

Since the collection of the ID is the first step in the construction of the map, the common interpretation of these instructions was that the map should be prepared at the beginning of the exam. Early preparation of the map reflects an attempt to follow Becker's idea (preparing evidence to facilitate large punishments), but distracts the proctors, and reduces the probability of punishments (e.g., warning and/or writing the name of students who appear to cheat) at the beginning of the exam.

The experiment compared two conditions. The experimental condition featured a minimal modification of the instructions to proctors that increases the proctor ability to follow a gentle COP policy (i.e., promptly warn students whose gaze was wandering). The manipulation was a change of the second instruction to the proctors to:

(2e) "A map of the students seating should be prepared 50 minutes after the beginning of the exam."

Seven undergraduate courses were selected to participate in the study. In all courses the final exam was conducted in two rooms. One room was randomly assigned to the experimental condition, and the second was assigned to the control condition. The only difference between the two conditions involved the timing of the preparation of the map in the instructions to the proctors. In the control group the instructions stated:

(2c) “A map of the students’ seating should be prepared immediately after the beginning of the exam.”

After finishing the exam, students were asked to complete a brief questionnaire in which they are asked to “rate the extent to which students cheated in this exam relative to other exams.” The results reveal large and consistent difference between the two conditions. The perceived cheating level was lower in the experimental condition in all seven comparisons.

4.3 Gentle COP 3: Broken windows theory, quality of life, and safety climate

In an influential paper, Kelling and Wilson (1982) suggest that physical decay and disorder in a neighborhood can increase crime rate. This suggestion, known as Broken Windows theory, was motivated by a field experiment conducted by Zimbardo (1969). The experiment focused on two cars that were abandoned in the Bronx, NY and in Palo Alto, CA. The results showed that vandalism of the cars started only after the experimenter created disorder (by removal of the license plate or breaking a window).

Broken windows theory was a motivation for the “quality of life” policing strategy implemented in New York City in the mid 1990’s (Kelling & Sousa, 2001). This policing strategy advocated increased number of police on the streets and arresting persons for less serious but visible offenses. Some credit this strategy for the decline in crime and disorder (Golub et al., 2002; Kelling & Sousa, 2001; Silverman, 1999). However, there are other explanations for the decline (see Eck & Maguire, 2000). Field studies that test the broken windows hypothesis provide mixed results. Skogan (1990) found that robbery victimization was higher in neighborhoods characterized by disorder, but Harcourt (2001) found that the crime-disorder relationship did not hold for other crime types including burglary, assault, rape and pick-pocketing.

We believe that the studies reviewed above can help clarify this mixed pattern. Under the current analysis, quality-of-life policing can be effective for the same reason that gentle COP policies are effective. When the probability of detection is very high, people learn to obey the rule. Thus, quality-of-life policing is effective in reducing robberies because these violations are more likely to be detected by the additional neighborhood police.

Luria, Zohar and Erev (2008) examined this "probability of detection" explanation in the context of safety-climate intervention (Zohar, 1980). Safety-climate interventions are very similar to quality-of-life policing. These interventions are designed to create a safer work climate. This goal is achieved by encouraging supervisors to exhibit commitment to safety (e.g., by measuring the number of times they discuss safety issues with their subordinates). Zohar (1980) and Zohar and Luria (2005) show that this manipulation increases safety. To test the probability of the detection hypothesis, Luria et al. reanalyzed the data reported in Zohar and Luria (2005). Their results show that the safety climate decreases unsafe behavior in environments with high visibility (the supervisor can detect rule violation with high probability), but not when visibility is low.

Notice that this explanation for the effect of quality-of-life has nontrivial positive and negative implications. On the positive side, this explanation implies that it may not be necessary to arrest all violators of minor crimes. If the probability of detection is high enough, more gentle punishment may be enough. For example, if the probability of detecting an attempt to use public transportation without paying is close to 1, then a fine that is only slightly larger than the regular cost should be sufficient. On the negative side, the current analysis suggests that quality-of-life policing is not likely to succeed when the probability of detection is low.

4.4. Gentle COP 4: Hand Washing

Hand washing is a nice example of the difference between decisions from experience and decisions from description. The consequence to failure to wash one's hands is potentially devastating—including serious illness or even death. The cost to washing one's hands is a few seconds of inconvenience. Everything we know about decisions from description—including risk aversion, loss aversion and overweighting of small probabilities—suggests that people would be eager to wash their hands. Yet, repeated experience following not washing one's hands is likely to result in no noticeable negative outcome and therefore in extinction of this desirable behavior. The effects we covered on learning, including underweighting of rate payoffs, recency, immediacy, and melioration, suggest that hand washing is a difficult behavior to maintain.

In 1847, Dr. Ignaz Semmelweis first demonstrated that routine hand-washing could prevent the spread of disease. In an experiment, Dr. Semmelweis insisted that his students staffing a Vienna hospital's maternity ward wash their hands before treating the maternity patients--and deaths on the maternity ward fell dramatically. In one case, it fell from 15% to near 0%!!. Though his findings were published, there was no apparent increase in hand washing by doctors until the discoveries of Louis Pasteur years after Dr. Semmelweis died in a mental asylum[13] (Nuland, 2003).

Moreover, many believe that even today medical professionals do not do enough on this front. In a recent study, Erev et al. (2010) used a variant of the gentle COP policy, described above, to increase the use of gloves by doctors and nurses. They focused on the use of gloves while taking blood and giving infusions in 12 distinct departments. The gentle intervention consistent of a single meeting with the department stuff. During this meeting the researchers suggested that the participants help each other remember to use gloves. That is, when they see a friend approach a patient without new gloves, they should ask him to fix the problem. The results show that this minimal manipulation increased glove use from 50% to 95%.

4.5 The effect of the timing of warning signals

Evaluation of the impact of warnings reveals a large effect of prior experience (see Barron, Leider & Stack, 2008). Individuals who have had good experiences in the past are less affected by the warning. For example, when the FDA added a black-box

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[13] According to some accounts, the fate of Dr. Semmelweis was a function of bid decisions. It seems that the influential heads of the departments who were responsible for the high and avoidable death rates were unhappy with his results.

warning to the drug Cisapride, the data show an *increase* in usage of 2% among repeat users, but a decrease of 17% amongst first-time users (Smalley, et. al., 2000). Another example is provided by a study of parent-adolescent sexual communication. Regular condom use was found to be lower when parent-adolescent sexual communication occurred at a later age (Hutchinson, 2002). Barron, Leider and Stack (2008) show that part of the effect of experience remains even after controlling for the available information. Indeed, experience reduces the tendency to respond to informative warnings even if the experience does not provide additional information. It seems that part of the effect of experience on the tendency to underweight warnings is a result of inertia.

4.6 Safety devices and the buying-using gap

The difference between decisions from experience and decisions from description suggests that in certain cases people may buy safety devices, but "learn" not to take the necessary measures to benefit from them. One example of this buying-using gap is a study by Yechiam et al. (2006) that focuses on car radios with a detachable panel. The detachable radio panel is an example of a safety device (against theft) that can be effective only when it is used (detached).

Notice that the main role of a detachable panel to a car radio is its value as a safety device. The decision not to detach the panel is made without explicit presentation and is likely to be shaped by repeated experience. Thus, the properties of decisions from experience imply decrease in the tendency to use the panel with experience, since the small probability of theft is underweighted. Yechiam et al. found (using a short survey) that the large majority (96%) of Israelis who bought car radios between 1995 and 2003 preferred the type with a removable panel even though it was remembered as being more expensive. Most participants detached the panel in the first two weeks, and were much less likely to detach it after a year. That is, responders behaved as if they gave more weight to the probability of theft in their initial use-decisions than in their use-decisions after a year of experience.

4.7 The effect of rare terrorist attacks

Previous studies reveal that even rare terrorist attacks can have large negative effects on international tourism. For example, following terrorist activity in Northern Ireland in the early 1970's, visitor arrivals fell from close to a million in 1967 to about 300,000 in 1976.

Yechiam, Barron & Erev (2005) note that the research reviewed above implies that other effects of terrorism may not be as large. Specifically, it implies a large difference between international and local tourism. Traveling to a different country requires a big decision from description. Local tourism, on the other hand, can be a product of small decisions from experience (e.g., whether to take a sandwich to work or dine in a restaurant) and can be affected by experience. Thus, with experience, the effect of rare terrorist attacks on local residents is likely to decrease.

Figure 16 presents the number of nights slept in Israeli hotels by local and international tourists before and after the beginning of the last wave of terrorist attacks in Israel (from September 2000). The results show a drop for both populations with the beginning of the recent attacks, but a quick recovery by local tourists. This trend is consistent with the suggestion that experience reduces the impact of rare attacks.

<Insert Figure 16>

Yechiam et al. note that their analysis suggests that the negative effects of rare terrorist attacks can be reduced by ensuring that citizens continue to partake in relatively safe leisure activities. Interestingly this suggestion summarizes one component of Mayor Rudolph Giuliani's response to the September 11 attack in New York City. Giuliani suggested that citizens should invest less in direct contributions (like helping digging and collecting blankets), and spend more time shopping and dining in New York. While this suggestion seemed counter-intuitive at the time, the current analysis suggests that it was effective in reducing the negative long-term economic effect of the attack.

4.8 Emphasis change training, flight school and basketball

Mane and Donchin (1989) have organized an interesting competition between leading researchers of motor skills learning. The participants in the competition were asked to develop a training method to improve performance in a complex "Space Fortress" video game. The human players in this game control a space ship and try to destroy a space fortress that tries to destroy their ship (using missiles and mines). High performance in this game requires sensitivity to several sources of information (e.g., the location of mines, the movement of missiles, the location of the ship, the angle of the ship's gun).

One of the most successful submissions to this competition, proposed by Gopher, Weil, & Siegel (1989), was based on the idea of "emphasis change training." During training, under this method, the trainees are continuously asked to change their focus. For example, they start by trying to maximize their scores on hitting the fortress, and then they are asked to focus on avoiding mines. The basic idea behind this method is simple: Under the assumption that people choose among multiple attention control strategies they are likely to converge to a local maximum (see Section 1.3.2). Emphasis change reduces the risk of this problem (see Erev & Gopher, 1998) by giving the trainee experience with attention control strategies she might not otherwise sample.

The emphasis change method was a clear winner in transfer tests (see Fabiani et al., 1989). One demonstration of the value of this method is provided by Gopher, Weil and Bareket (1994). In the experimental group of their study, cadets in flight school were asked to play the space fortress game and practiced using the emphasis change training method. The results reveal that this experience had large positive effect on their subsequent performance in flight school. The probability of successful completion of the course increased by 33%.

Another demonstration of the value of emphasis change training is provided by the success of a commercial variant of the space fortress game (see www.intelligym.com), designed to facilitate attention control by basketball players. The commercial product was used by only two NCAA men's basketball teams in 2005: the University of Memphis and the University of Florida. Florida won the NCAA title in both the 2005/06 and 2006/07 seasons. Twelve NCAA teams used the emphasis change trainer in the 2007/08 season: one of them (University of Kansas) won the title and another user (University of Memphis) was the runner-up.

4.9 The pat-on-the-back paradox

Informal rewards, often referred to collectively as “pats-on-the-back,” are low cost or no cost, often verbal, rewards that have virtually no monetary market value. Psychological research has shown that “pats on the back,” can be as motivating as monetary awards. For example, Stajkovic and Luthans (1997) present a meta-analysis of 19 studies showing that feedback and social reinforcers may have as strong an impact on performance as pay. Survey-based data suggest similar conclusions. In a survey of American workers, 63% indicated a pat-on-the-back to be an effective incentive (Lovio-George, 1992). In other survey-based studies (Graham & Unruh, 1990), pat-on-the-back incentives are shown to be more effective than monetary rewards. Such findings are often attributed to the recognition bestowed by the pat on the back and have prompted statements such as: "There are two things people want more than sex and money ... recognition and praise" (Nelson, 1994, quoting Mary Kay Ash, founder of Mary Kay Cosmetics).

These results appear to be inconsistent with the observation that most job postings focus on the salary, opportunities, and the possibility of promotion and professional development, and not on the likelihood of pats on the back. We believe that this “pat-on-the-back paradox” can be resolved as a reflection of the differential weighting on rare events in decisions from experience and from description. This explanation is based on the assumption that the probability of attractive events (like promotions and bonuses) in the typical workplace is low. Thus, these events are overweighted when considering a description of the job, but are underweighted in decisions from experience. Underweighting of these rewards is expected to reduce effort in the workplace. To address this problem, wise managers use pats-on-the-back as “lottery tickets” that signal a probabilistic future value (like a possible promotion), which makes the reinforced behavior attractive.

4.10 Gambling and the medium prize paradox

According to the leading explanations of gambling, people gamble because they overweight rare events (Kahneman & Tversky, 1979) or because they are risk seekers around the status quo (Savage & Friedman, 1948). These explanations can explain the popularity of gambling games that promise positively skewed payoff distributions that provide very high payoffs with very low probability. However, they appear to be inconsistent with the observation that a large proportion of the payoffs in many gambling games involve medium prizes. Medium prizes are particularly common in casino settings.

Haruvy Erev and Sonsino (2001, following Skinner, 1953) suggest that the co-existence of high and medium prizes can be a response to two behavioral biases: Overweighting of rare events in decisions from description, and the payoff variability effect in decisions from experience. High prizes are necessary to attract new gamblers (who respond to a description of the game), and medium prizes are necessary to increase the payoff variability that slows learning (that this sort of gamble is costly).

4.11 The evolution of social groups

Recent research demonstrates that two of the most basic observations from studies of the development of social groups can be a product of the hot stove effect. Denrell (2005) focuses on the observation that proximity is an important determinant of liking (Brewer & Campbell, 1976; Festinger, Schachter, & Back, 1950; Segal, 1974). Even if students are randomly assigned to rooms, individuals are more likely to become friends with and have a favorable impression of individuals who are nearby (Segal, 1974). Denrell's explanation is simple and elegant: our opinions about our friends are likely to change after each meeting. When these opinions determine the probability of future meeting, we will stop meeting a friend when we no longer like him (and keep our low opinion). This problem is less severe when the proximity is high. For example, roommates meet independently of changes in their contemporary opinions. Thus, proximity eliminates the problematic hot stove effect in this setting.

Denrell and Le Mens (2007) extend this analysis and show that the hot stove effect can explain the observation that friends holds similar beliefs. This observation is based on the assumption that low evaluation of an activity (like eating at a particular restaurant, or attending service at a particular church) decreases the probability of a repetition of this activity. Friendship slows this process because high evaluation by a friend can lead us to repeat activities even when our personal evaluation is low.

Another example of a possible effect of decisions from experience to the development of social groups involves the survival of sects and religious groups that demand significant sacrifice. As noted by Berman (2001) successful groups appear to create an incentive structure in which the cost of exiting the group increases over time. Thus, melioration and related properties of decisions from experience can be among the contributors to the success of these groups.

4.12 Product updating

Consumers have long been known to exhibit inertia in moving from one technology standard to another, even when the newer standard is demonstrably superior (Clements, 2005; Gourville, 2003). Microsoft, for example, the largest and most successful computer software company, is often criticized on the grounds that its products are inferior to competitors' products. Nevertheless, Microsoft products are often dominant in the market. While the reasons behind Microsoft's dominance are complicated and numerous (including the importance of establishing a network of users, complementarities, and unfair anti-competitive practices by Microsoft), research on consumption of other experience goods (products that require consumption before knowing their quality) has shown that consumers who behave as hill climbers will be unable to move easily from the old to the new product and will often converge to a local maximum.

Consumer learning in experience goods markets has been an important subject of theoretical research in industrial organization and marketing since the 1970's. Learning can be an especially important factor in the demand for new products, and there is an empirical literature that quantifies learning in household panel data for grocery purchases (for example, Erdem & Keane, 1996), choice between personal computers (Erdem, Keane & Oncu, 2005), and choice between drugs (Crawford & Shum, 2005). In these papers, it is assumed that the only type of dynamics in demand comes from learning, and the learning explanation is shown to explain the inertia that might explain the reluctance of Microsoft consumers to switch to superior products. Gourville (2003) likewise attempts to understand why many consumers do not immediately switch from a product they currently use to the latest innovative improved product, even if the cost difference is minimal. He finds support for the basic learning assumptions we described in this work: Consumers are sensitive to relative payoffs of the two products and their reference points about each product's quality critically depend on past experience. Local hill-climbing can therefore take consumers to a suboptimal product choice.

4.13. Unemployment

The decision to accept a particular job offer is often not a small decision. The stakes are usually high, and the decision maker is likely to invest time and effort in this choice. Nevertheless, many small decisions are likely to affect the employment status of the decision maker. Examples include the decisions to invest effort in particular tasks in school, at work, and while looking for a job. These small decisions are likely to affect the likelihood of receiving attractive job opportunities.

Lemieux and MacLeod (2000) present an elegant analysis that demonstrates how the basic properties of learning, reviewed above, can shed light on an apparently weak relationship between unemployment rates and public policies. They focus on the unemployment rate in Canada in the period of 1972-1992. The Canadian unemployment insurance system greatly increased benefits to the unemployed in 1971. The generosity of the unemployment insurance did not increase again, but unemployment steadily increased from 1972 to 1992. Lemieux and MacLeod note that this pattern can be captured with the assertion that the description of the incentive system has limited effect. The main effect is a result of personal experience with the new incentives.

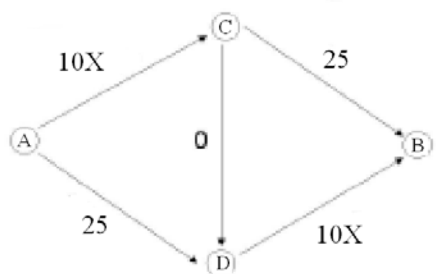
4.14 The second-order Braess paradox

The Braess paradox (Braess, 1968) is a simple illustration of how it is possible to add capacity to a traffic network and make everyone's journey time (at equilibrium) worse than it was previously. That is, by adding a road to an existing traffic system of roads, all drivers' travel time increases.

The example below comes from Rapoport, Kugler, Dugar and Gisches (2008). The numbers next to each line denote the driving time it takes to travel the line. X denotes the number of drivers. Thus, the driving time increase with the number of users in two of the roads (A-C and B-D), but not in the other two. The addition of a road C-D that connects point C with point D increases the driving time from A to B in equilibrium.

Suppose there are two players. It is easy to verify that there are two pure-strategy equilibria in the network without road C-D, has one player choosing the route A-C-B and the other choosing A-D-B. The cost of travel in this case is 10+25=35. No player benefits from unilateral deviation.

Consider next the augmented network with the additional road CD. It is again easy to verify that the augmented network has unique pure-strategy equilibrium where the two players choose the route (A-C-D-B) for total travel cost of 20+0+20=40. The counterintuitive feature of this example is that the improvement of the network in the basic network by adding a cost-free link C-D causes every network user to be worse off by 14.3 percent (5/35) of the original travel cost.



An experimental study of the Braess paradox (see Rapoport, Kugler, Dugar & Gisches, 2008) shows slow convergence to this problematic equilibrium prediction. The current analysis suggests an even slower adaptation process in natural settings when the players (drivers) have more options (e.g., more roads, other means of transportation, and different commuting times). This pattern implies that, in many cases, new roads have a short-term positive effect even when their overall effect is negative. The discrepancy between the short and the long term implies a second-order Braess paradox: It is possible that policy makers will not respond to the original paradox. That is, they will not notice, or will not be motivated to notice (because they are evaluated on short term accomplishments), that the addition of certain roads is counter-productive.

4.15 Interpersonal conflicts and the description-experience gap

Review of previous research of interpersonal conflicts reveals an apparent inconsistency between the main conclusions of two lines of research. On one hand, mainstream research in behavioral game theory highlights the importance of other regarding preferences (see Fehr & Schmidt, 1999; Bolton & A Ockenfels, 2000; Charness & Rabin, 2002, and see review in Cooper & Kagel, 2008). This research suggests that people pay more attention to the incentives of others than predicted under the rationality assumption. On the other hand, negotiation research reflects "mythical fixed pie beliefs" (see Bazerman & Neal, 1992) that imply the opposite bias: A tendency to ignore the incentives of others and assume that efficient cooperation or coordination is impossible.

Erev and Greiner (in press) suggest that this apparent inconsistency can be a product of the difference between decisions from description and decisions from experience discussed above. It is possible that social behavior reflects oversensitivity to the outcomes of others when these outcomes are described (the convention in mainstream behavioral economic research), but reflects the basic properties of decisions from experience when the outcomes are not clearly described (the state in most negotiation settings). The basic properties of decisions from experience, in turns, imply a tendency to exhibit insufficient sensitivity the payoff of other agents.

Erev and Greiner clarify this assertion with the study of the 5x5 a-symmetric Stag Hunt game presented in Table 9. Notice the game has two equilibrium points: The “E, E” equilibrium is efficient (payoff dominant) and fair: Both players win 12 (joint payoff of 24) under this equilibrium. The “A, A” equilibrium is inefficient (joint payoff of 15), and unfair (one player wins 10, and the other wins 5), but it is the risk-dominant equilibrium. The game was played repeatedly (for 50 trials), with fixed matching, under two information conditions. The participants receive complete description of the matrix in Condition Description, but not in condition Experience. The results reveal large difference between the two conditions. The modal outcome was efficient and fair (E,E -- as predicted by other regarding preferences) in Condition Description, and inefficient and unfair (A,A -- as predicted by the basic properties of decisions from experience) in Condition Experience.

The current analysis leads to optimistic predictions: It implies that manipulations that increase exploration (like the emphasis change procedure) can increase social efficiency. This prediction is consistent with the main idea of popular negotiation books.

4.16 Implications for financial decisions.

Typical financial decisions often involve high stakes. Nevertheless, several lines of recent research demonstrate interesting similarity between financial decisions and the experimental literature reviewed here.

The best known example is provided by Taleb’s (2007) prediction of the 2008 financial crisis. Taleb used the tendency to underweight rare events in decisions from experience, reviewed above, to justify his "black swan" assertion, according to which investors tend to dismiss low probability events. For that reason, low probability events, when they occur, can lead to financial crises.

Another example involves the assertion that many investors have under-diversified investment portfolios (e.g., Blume and Friend, 1975; Kelly, 1995). Ben Zion et al. (2010) show that this tendency can be observed in the clicking paradigm, and can be a product of the tendency to rely on past experiences.

A third example concerns with the observed sequential dependencies in stock markets. Empirical analyses reveal high correlation between absolute price change in a particular trading day and volume of trade in the following day (see Karpoff, 1988). Nevo and Erev (2012) show that this pattern can be a product of the surprise-trigger-change of decisions from experience.

4.17. Summary and the innovations--discoveries gap.

The first author of the current chapter was recently invited to give a talk in a lecture series with the title "Inventions and discoveries that have shaped the human civilization." While preparing the talk he noticed of a surprising large gap between his favorite examples of inventions and of discoveries in economics. Whereas the most influential inventions (e.g., markets, money, banks, rules, credit cards, auctions, e-trading) are based on the assumptions that people try to maximize expected return, the best-known discoveries focus on deviations from rational behaviors.

We believe that the results reviewed above highlight one contributor to this gap. The basic properties of decision from experience imply interesting deviations from maximization, but also imply a wide set of situations in which people behave as if they are trying to maximize expected return: When the strategy that maximizes expected return also lead to the best outcome most of the time, people exhibit high sensitivity to the incentive structure. (This prediction is clarified by I-SAW: When the best alternative is also best most of the time, the "grand mean" and the "sample mean" tend to point in the same direction). It seems that many of the successful economics innovations are mechanisms that increase the probability that the socially desired behavior will be reinforced on average, and most of the time.

Most of the applications considered above follow a similar logic. They start with the discovery of a problematic deviation from maximization that can be the product of the tendency to rely on small samples, and then show that the problem can be addressed by a change of the incentive structure that increase the probability that the desired behavior will be reinforced on average, and most of the time.

5. Conclusion

The research reviewed here can be summarized by six main sets of observations. The first set includes demonstrations the generality of basic properties of decisions from experience. The patterns described here have been observed in animals, laboratory student subjects engaging in simple tasks, and in relatively complex social interactions. An additional indication of the robustness of the main results is provided by the observation that they can be summarized with a simple model (best reply to a small sample of experiences in similar situations) that allows for useful (high ENO) ex ante quantitative prediction of behavior in new situations.

A second set of observations involves two shortcomings of an approach based on the strictest interpretation of rationality—including equilibrium analysis. First, there are many situations in which this approach is “not even wrong.” For example, this approach does not provide a clear prediction of behavior in the clicking paradigm. Almost any behavior can be justified as “rational” given certain prior beliefs. Second, when the rationality assumption can be wrong, it is often wrong at the intermediate term. For example, learning away for a mixed strategy mixed-strategy equilibria persists for at least 500 trials (see Section 3.2), and learning away from a simulated index fund that is known to maximize expected payoff and minimize variance experience persists for at least 100 trials (see Section 1.3.1). It is important to recall, however, that the current results do not reject epsilon equilibrium models (e.g., Radner, 1980; McKelvey and Palfrey, 1995). Indeed, the descriptive models presented above are members of the class of epsilon equilibrium models: When the incentive structure is strong enough (in the way implied by these models), they imply an approximation of the optimal behavior.

A third set involves the conditions under which experience leads decision makers toward maximization of expected return (and risk neutral equilibrium). High maximization rate was documented when the strategy that maximizes expected return also lead to the best outcome most of the time. Similarly, convergence to mixed strategy equilibrium was observed when the choice proportions at equilibrium are consistent with the proportions of times in which each alternative leads to the best outcomes.

A fourth set of observations concern the difference between decisions from experience and decisions from description. The results described here suggest that decision makers underweight rare events in decisions from experience, but overweight rare events in decisions from description (see Section 1.1.3). Another example of this difference is the apparent inconsistency between research documenting other regarding behavior, and the finding that some social conflicts reveal the opposite bias (See Section 3.15).

The fifth set pertains to the distinction between basic learning properties and other cognitive factors that affect the impact of experience. The current review suggests that the effects of other cognitive factors are important, but are less general than the basic properties of learning. For example, the indications for learning to follow a reciprocation strategy in a repeated prisoner dilemma game are highly sensitive to the framing of the task.

Finally, the current review suggests that the study of decisions from experience may shed light on many interesting economic phenomena. Highly consequential economic phenomena may be the result of small and relatively inconsequential decisions by many individuals. The applications presented in Section 3 suggest that experimental research on small decisions can be used to understand larger phenomena and facilitate efficient design of relevant incentive structures.

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Table 1: Summary of experiments that examine a choice between a safe prospect and a prospect with no more than 2 outcomes using the basic clicking paradigm. The recency effects (in bold) are estimated as the difference between the R-rates after high and low payoffs from R given the same recent choice.

			Experimental results					The predictions of I-saw				
			R-rates and implied recency effect as a function of last choice and recent payoff from R				R-rate over all trials	R-rates and implied recency effect as a function of last choice and recent payoff from R				R-rate over all trials
								Last choice				
		Last choice	S (R-rate is switch rate, recent payoff from R is forgone)		R (R-rate is repetition rate, recent payoff from R is obtained)			S (R-rate is switch rate, recent payoff from R is forgone)		R (R-rate is repetition rate, recent payoff from R is obtained)		
Problem [# of trials]		Most recent payoff from R	High	Low	High	Low		High	Low	High	Low	
1 [200]	S 0 with certainty R 1 with certainty	R-rate	.43	-	.99	-	.96	0.48	-	0.94	-	0.89
			-		-			-		-		
2 [200]	S 0 with certainty R (11, .5; -9)	R-rate	.56	.21	.81	.59	.58	0.37	0.30	0.81	0.76	0.61
		Recency	**+.35**		**+.22**			**+.07**		**+.05**		
3 [200]	S 0 with certainty R (9, .5; -11)	R-rate	.40	.16	.77	.60	.47	0.24	0.18	0.72	0.64	0.40
		Recency	**+.24**		**+.17**			**+.06**		**+.08**		
4 [100]	S 0 with certainty R (10, .1; -1)	R-rate	.23	.06	.60	.79	.29	0.32	0.13	0.74	0.76	0.38
		Recency	**+.17**		**-.19**			**+.19**		**-.02**		
8 [100]	S 0 with certainty R (1, .9; -10)	R-rate	.21	.31	.84	.69	.56	0.24	0.26	0.87	0.68	0.62
		Recency	**-.10**		**+.15**			**-.02**		**+.19**		
9 [400]	S 3 with certainty R (4,0.8; 0)	R-rate	.2	.20	.91	.67	.64	0.36	0.38	0.85	0.76	0.68
		Recency	**+.06**		**+.24**			**-.02**		**+.09**		
12 [400]	S 2.52 with certainty R (2.53,0.89; 2.43)	R-rate	.15	.09	.94	.78	.60	0.28	0.30	0.85	0.72	0.63
		Recency	**+.06**		**+.16**			**-.02**		**+.13**		
13 [400]	S 2.52 with certainty R (2.53,0.89; 2.03)	R-rate	.06	.08	.92	.63	.28	0.08	0.08	0.76	0.57	0.24
		Recency	**-.02**		**+.29**			**0**		**+.19**		
14 [100]	S 7 with certainty R (16.5,0.01;6.9)	R-rate	0.40	0.04	0.94	0.95	0.45	0.46	0.07	0.77	0.91	0.46
		Recency	**+.36**		**-.01**			**+.39**		**-.14**		
15 [100]	S -9.4 with certainty R (-2,0.05;-10.4)	R-rate	0.15	0.06	0.70	0.80	0.26	0.23	0.09	0.56	0.71	0.26
		Recency	**+.09**		**-.10**			**+.14**		**-.15**		
16 [100]	S -4.1 with certainty R (1.3,0.05;-4.3)	R-rate	0.27	0.06	0.86	0.94	0.54	0.36	0.11	0.81	0.84	0.42
		Recency	**+.21**		**-.08**			**+.25**		**-.03**		
17 [100]	S -18.7 with certainty R (-7.1,0.07;-19.6)	R-rate	0.29	0.06	0.85	0.87	0.38	0.31	0.11	0.72	0.76	0.35
		Recency	**+.23**		**-.02**			**+.20**		**-.04**		
18 [100]	S -7.9 with certainty R (5,0.08;-9.1)	R-rate	0.20	0.06	0.86	0.84	0.31	0.30	0.12	0.71	0.75	0.34
		Recency	**+.14**		**+.02**			**+.18**		**-.04**		
19 [100]	S -25.4 with certainty R (-8.9,0.08;-26.3)	R-rate	0.22	0.07	0.89	0.90	0.45	0.35	0.13	0.82	0.83	0.46
		Recency	**+.15**		**-.01**			**+.22**		**-.01**		
20 [100]	S 11.5 with certainty R (25.7,0.1;8.1)	R-rate	0.29	0.07	0.81	0.78	0.30	0.23	0.11	0.60	0.67	0.26
		Recency	**+.22**		**+.03**			**+.12**		**-.07**		
21 [100]	S -15.5 with certainty R (-8.8,0.6;-19.5)	R-rate	0.42	0.19	0.91	0.75	0.68	0.44	0.39	0.90	0.86	0.77
		Recency	**+.23**		**+.16**			**+.05**		**+.04**		
22 [100]	S 2.2 with certainty R (3,0.93;-7.2)	R-rate	0.13	0.15	0.85	0.68	0.47	0.25	0.30	0.89	0.71	0.67
		Recency	**-.02**		**+.17**			**-.05**		**+.18**		
23 [100]	S 25.2 with certainty R (26.5,0.94;8.3)	R-rate	0.14	0.32	0.86	0.82	0.52	0.25	0.31	0.90	0.71	0.68
		Recency	**-.18**		**+.04**			**-.06**		**+.19**		
24 [100]	S 6.8 with certainty R (7.3,0.96;-8.5)	R-rate	0.08	0.23	0.92	0.77	0.50	0.16	0.21	0.90	0.65	0.60
		Recency	**-.15**		**+.15**			**-.05**		**+.25**		
25 [100]	S 11 with certainty R (11.4,0.97;1.9)	R-rate	0.09	0.19	0.94	0.71	0.57	0.19	0.33	0.92	0.70	0.68
		Recency	**-.10**		**+.23**			**-.14**		**+.22**		

Table 2: The proportion of risky choices as a function of feedback and time (in two blocks of 50 trials) in 12 randomly selected problems that were studied using the clicking paradigm. The complete feedback condition was run by Nevo and Erev (2012), and the partial feedback condition was run by Erev et al. (2010). The difference column is an estimate of the hot stove effect.

Problem		Block	Complete	Partial	Difference
14	S 7 with certainty R (16.5,0.01;6.9)	1	0.45	0.21	0.24
		2	0.46	0.15	0.31
15	S -9.4 with certainty R (-2,0.05;-10.4)	1	0.27	0.16	0.11
		2	0.25	0.07	0.18
16	S -4.1 with certainty R (1.3,0.05;-4.3)	1	0.51	0.31	0.20
		2	0.58	0.29	0.29
17	S -18.7 with certainty R (-7.1,0.07;-19.6)	1	0.37	0.35	0.02
		2	0.39	0.33	0.06
18	S -7.9 with certainty R (5,0.08;-9.1)	1	0.41	0.24	0.17
		2	0.49	0.14	0.35
19	S -25.4 with certainty R (-8.9,0.08;-26.3)	1	0.29	0.11	0.18
		2	0.32	0.07	0.25
20	S 11.5 with certainty R (25.7,0.1;8.1)	1	0.31	0.12	0.19
		2	0.28	0.11	0.17
21	S -15.5 with certainty R (-8.8,0.6;-19.5)	1	0.65	0.62	0.03
		2	0.71	0.69	0.02
22	S 2.2 with certainty R (3,0.93;-7.2)	1	0.48	0.52	-0.04
		2	0.46	0.35	0.11
23	S 25.2 with certainty R (26.5,0.94;8.3)	1	0.54	0.65	-0.11
		2	0.49	0.42	0.07
24	S 6.8 with certainty R (7.3,0.96;-8.5)	1	0.54	0.70	-0.16
		2	0.47	0.60	-0.13
25	S 11 with certainty R (11.4,0.97;1.9)	1	0.61	0.69	-0.08
		2	0.53	0.63	-0.10

Table 3: The basic Markov chain used by Biele et al. (2008). The entries present the transition probabilities between the two states of nature (L and H) for the risky option R.

		Trial t +1	
		H	L
Trial t	H	p	1-p
	L	q	1-q

Table 4: Three of the randomly selected games studied by Erev et al (2002, 2007) under minimal information (unknown matrix, feedback limited to obtained payoffs) and under full information (known matrix, complete feedback). The games are presented on the left (the entries in each cell are the probability that Player 1 wins, the probability that Player 2 wins is 1 minus this value). The right hand columns present the equilibrium prediction, the observed results (over the 500 trials, by condition), and the predictions of I-SAW. The correlation between the two conditions is 0.9, the correlation between I-SAW and the full information condition is 0.93 and the MSD score is 0.0047.

Game						Information condition		I-SAW
		A2	B2	Statistic	Eq.	Minimal	Full	I-SAW
1	A1	.77	.35	P(A1)	.49	0.68	0.59	0.64
	B1	.08	.48	P(A2)	.16	0.42	0.32	0.28
2	A1	.73	.74	P(A1)	.99	0.76	0.84	0.84
	B1	.87	.20	P(A2)	.79	0.40	0.36	0.21
9	A1	.40	.76	P(A1)	.65	0.58	0.56	0.61
	B1	.91	.23	P(A2)	.51	0.45	0.45	0.46

Table 5: Prisoner dilemma games that were studied using variants of Selten and Stoker's supergame procedure

PD2: Selten & Stoker		C	D
	C	60, 60	-50, 145
	D	145, -50	10, 10
PD3: Andereoni & Miller		C	D
	C	7, 7	0, 12
	D	12, 0	4, 4
PD4: Bereby-Meyer & Roth		C	D
	C	.105, .105	.005, .175
	D	.175, .005	.075, .075
PD5: Dal Bó and Fréchette		C	D
	C	R, R	12, 50
	D	50, 12	25,25

Table 8: The asymmetric Stag Hunt game considered by Erev and Greiner (in press)

	A	B	C	D	E
A	10, 5	9, 0	9, 0	9, 0	9, 0
B	0, 4	0, 0	0, 0	0, 0	0, 0
C	0, 4	0, 0	0, 0	0, 0	0, 0
D	0, 4	0, 0	0, 0	0, 0	0, 0
E	0, 4	0, 0	0, 0	0, 0	12, 12

Figures

Figure 1. The typical instructions screen in studies of decisions from description (using the "decisions under risk paradigm"), and studies of decisions from experience (using the "clicking paradigm"). In the decisions under risk paradigm the subjects receive a complete description of the payoff distributions, and no feedback. Each selection moves the subject to the next task.

In the clicking paradigm, the subjects do not receive a description of the payoff distribution, and have to rely on the available feedback. In the experiments described in Section 1.1, the feedback was complete: It included information concerning the payoffs from both keys. In the experiments described in Section 1.2 the feedback was partial: only the payoff from the selected option was revealed.

a. Decision from description -- the decisions under risk paradigm:

Please select one of the following prospects:

○	Win 4000 with probability 0.80 0 otherwise (probability 0.20)
○	Win 3000 with certainty

b. Decisions from experience -- the clicking paradigm:

The current experiment includes many trials. Your task, in each trial, is to click on one of the two keys presented on the screen. Each click will be followed by the presentation of the keys' payoffs. Your payoff for the trial is the payoff of the selected key.

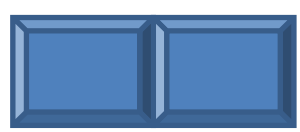


Figure 2: The H-rate (proportion of H choices) of three participants in the first 25 trial of an experiment that involves a choice between a key that provides 1 with certainty (Option H), and a key that provides 0 with certainty. Each curve presents the H-rate of one participant in 5 blocks of 5 trials each. All subjects learn to maximize, but the process is stochastic.

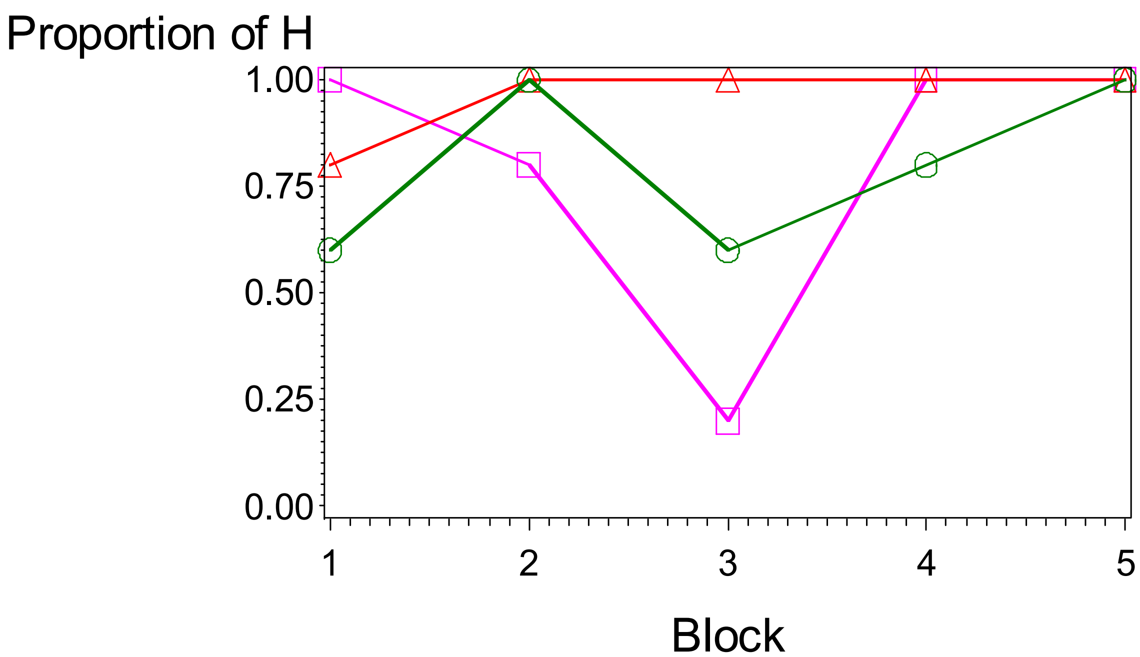


Figure 3. Proportion of H choice in Problems 1,2, and 3 in 10 blocks of 20 trials. The results demonstrate the payoff variability effect.

Problem	H (high EV)	L
1	1 with certainty	0 with certainty
2	(11, .5; -9)	0 with certainty
3	0 with certainty	(9, .5; -11)

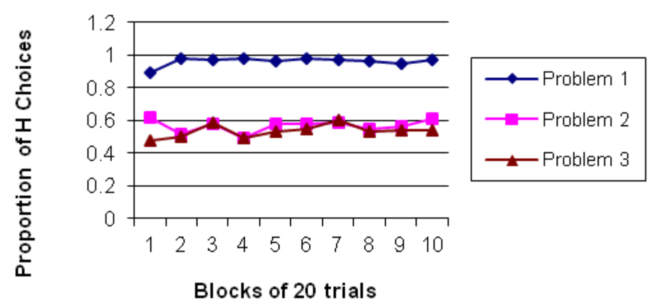


Figure 4: The very recent effect: The proportion of choices (at trial t) of the alternative that led to the best outcome in trial t-Lag. Thus, Lag=1 (on the right) present the best reply rate to the most recent trial, and Lag=2 present the best reply rate to the outcome occur in the trial before the most recent. The analysis is based on trial 21 to 200 in Problems 2 and 3.

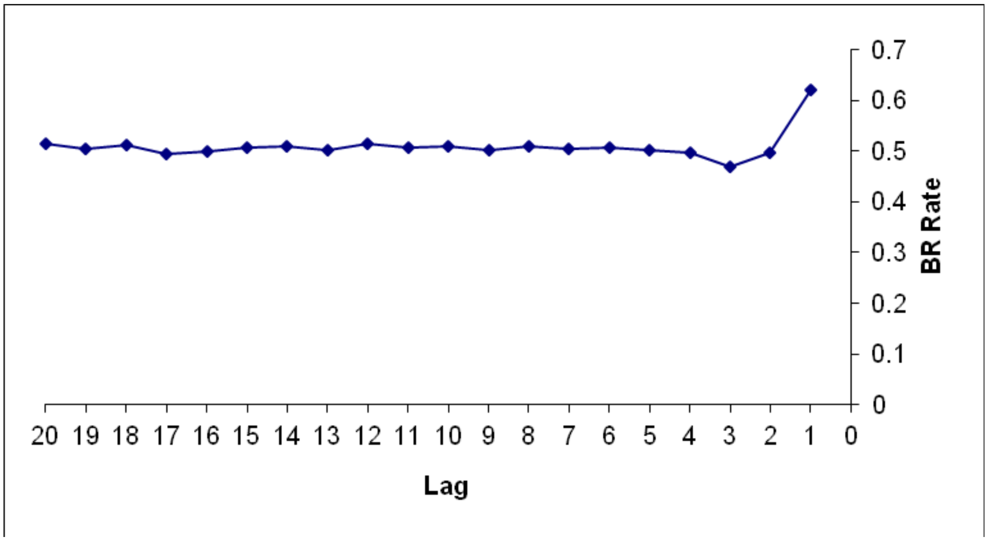
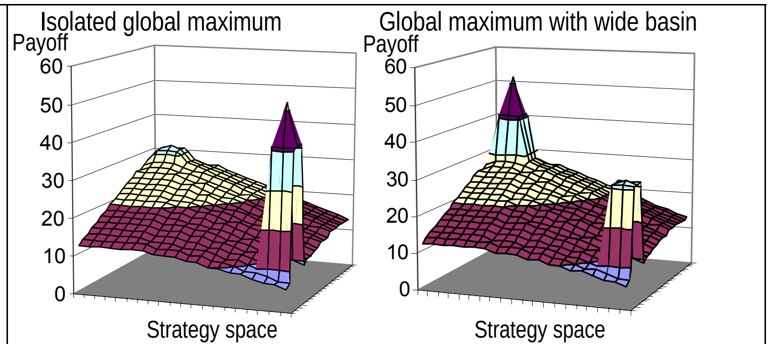


Figure 5: A demonstration of the neighborhood effect. In each trial the participants were asked to select one of 400 keys that were presented in a 20X20 matrix. The upper panel presents the payoff matrix. The lower payoff presents the proportion of the maximal payoff (Pmax) obtained by the subject in 4 blocks of 50 trials.

Three dimensional summary

of the payoff matrices



Pmax in blocks of 100 trials

(minimal information, 400 trials, n=10, .25¢):

Problem 26: Isolated G. max

Problem 27: G. max. with wide basin

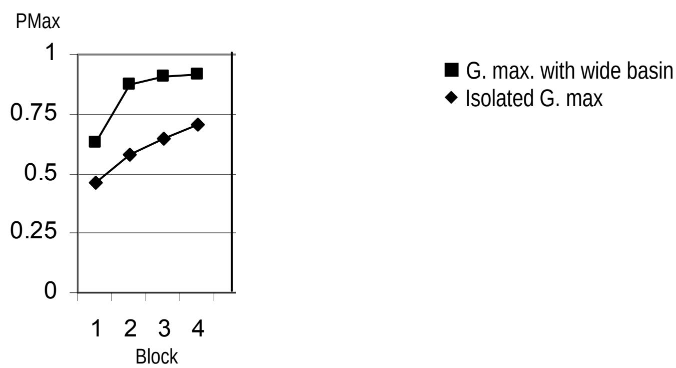


Figure 6. The choice proportions observed in Biele et al.'s (2008) examination of the two variants of Problem 28.

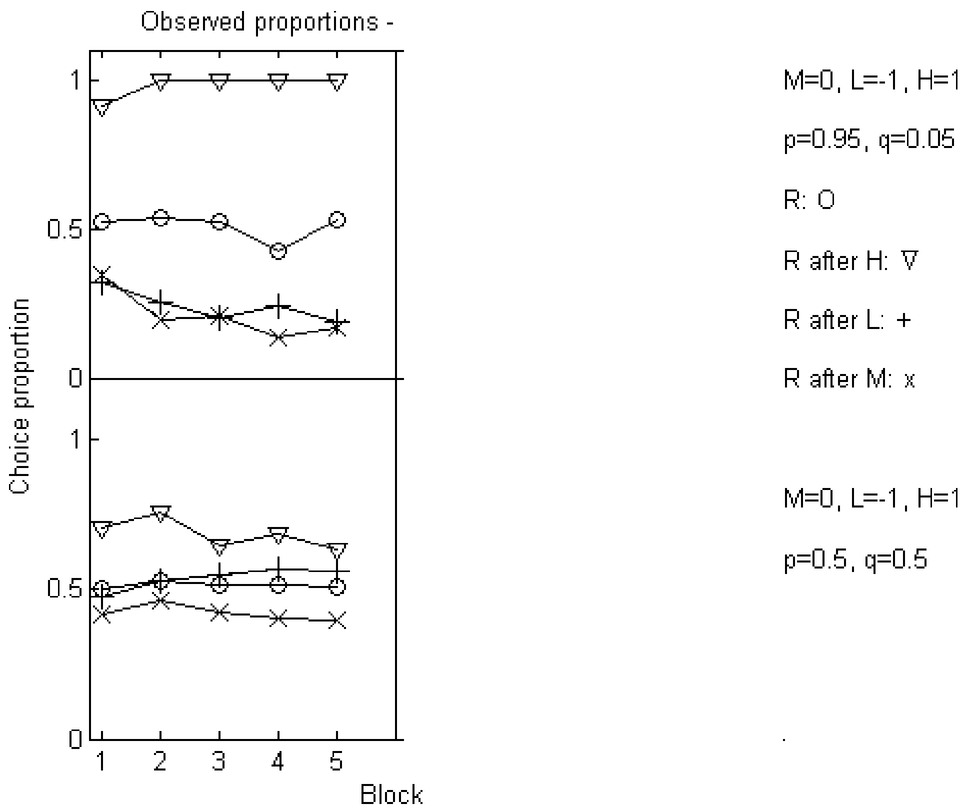


Figure 7. A demonstration of the partial reinforcement extinction effect (PREE, from Hochman and Erev, 2007). In the first 100 trials the continuous group faced Problem 30, and the partial group faced Problem 31. Both groups faced Problem 32 in the last 100 trials. The results reveal faster learning and faster extinction in the continuous group.

Problem	S	R
30	8 with certainty	9 with certainty
31	8 with certainty	(1,.5; 17)
32	8 with certainty	1 with certainty

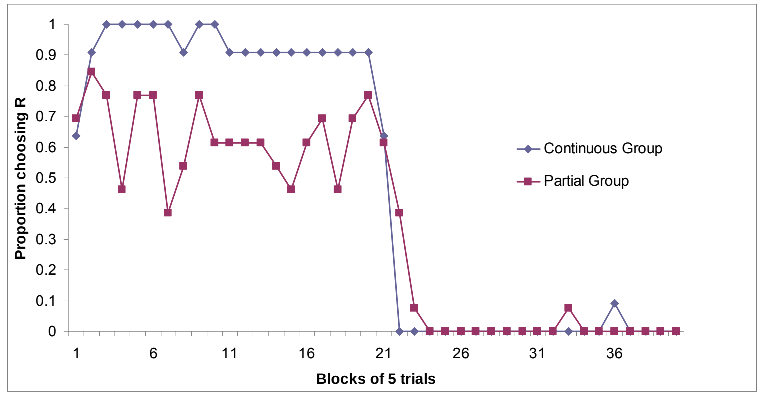


Figure 8: Mutual fate game. Mutual Fate Control game (left) and experimental results of Colman et al (2010) (right): Proportions of cooperative choices over four trial blocks in groups of varying sizes. Error bars represent standard errors.

	C	D
C	1,1	0,1
D	1,0	0,0

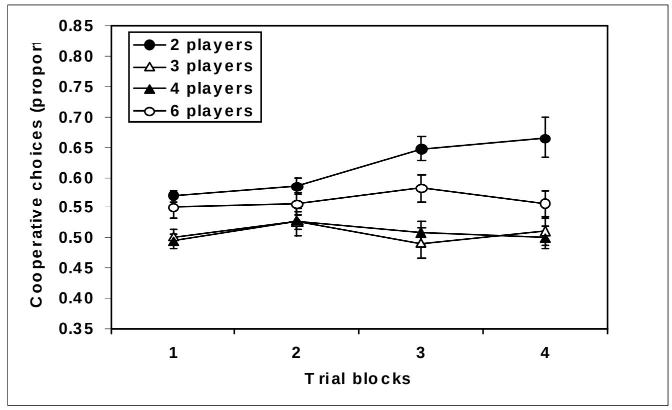


Figure 9: A constant sum game study (Suppes and Atkinson, 1960). In each trial Player 1 selects a row and Player 2 selects a column. The selected cell determines the players' payoff: Player 1's payoff is the entry on the left, and Player 2's payoff is the entry on the right. The left-hand graphs present the observed proportion of A1 and A2 choices, and the equilibrium predictions (as a separate point in the last block). The results reveal that player 1 deviates from the equilibrium prediction.

	A2	B2
A1	0.3,0.7	0.8,0.2
B1	0.4,0.6	0.1,0.9

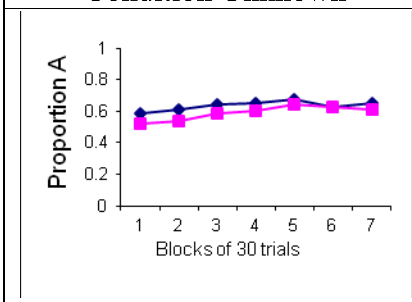
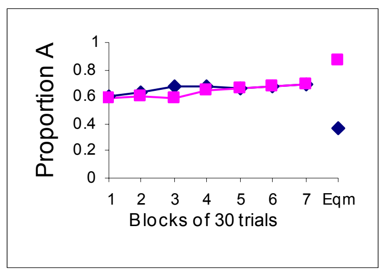
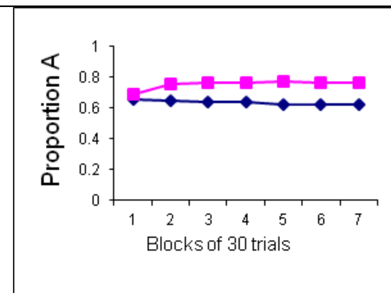
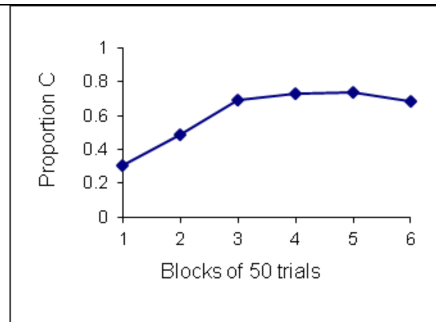
Condition Unknown	Condition Known	I-SAW
		

Figure 10: Two studies of a Prisoner's dilemma game. Rapoport and Chammah examine repeated play with fixed matching. Daniely examined the same game with fixed and random matching. The observed results reveal increase in cooperation over time with fixed matching.

Game (Payoff matrix)	Observed

Rapoport & Chammah (1965)



PD1	C	D
C	1,1	-10,10
D	10,-10	-1,-1

Daniely (2000)

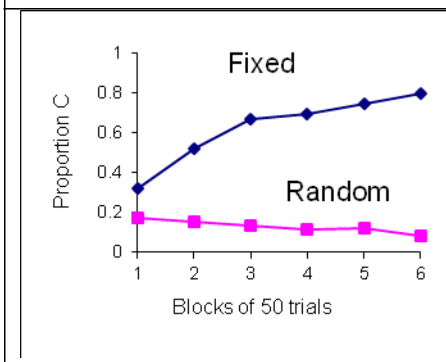


Figure 11: Percentage of workers that obey the safety rule and use the required safety equipment as a function of time in one of the departments studied by Erev and Rodensky (2004). The baseline data were collected a month before the beginning of the intervention (in September 2003).

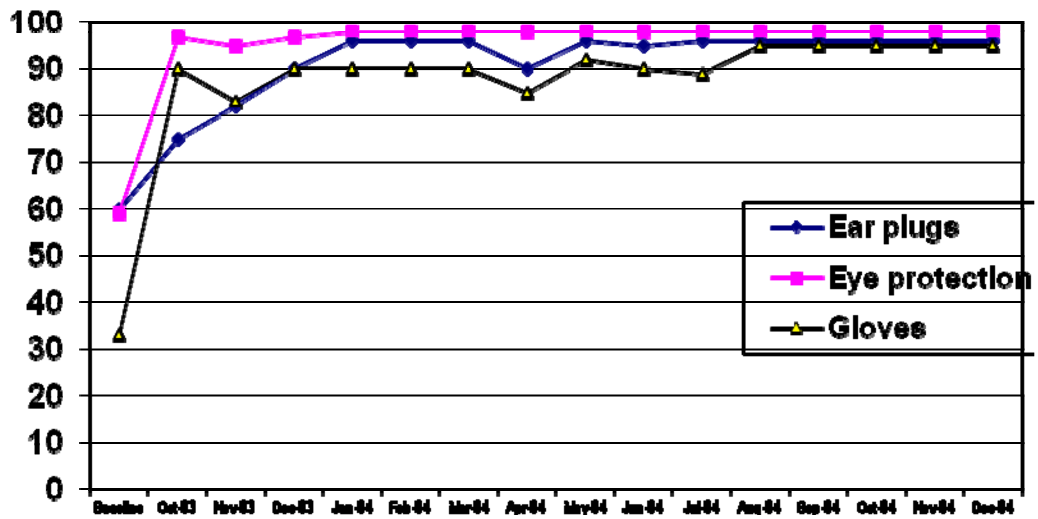


Figure 12: Bed nights in tourist hotels in Israel from January 1997 to August 2002: seasonally adjusted average (dashed line) and trend by 1,000 bed nights (ICBS, 2002b. used with permission).