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Author(s)*: Tibor Neugebauer, Daniela Di Cagno, Carlos Rodriguez-Palmero, Abdolkarim Sadrieh

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JEL Classification : C90, D53, D92, G02, G11, G12

***Corresponding Author's Address:** Tel: +352 46 66 44 6285; Fax : +352 46 66 44 6835
E-mail address: tibor.neugebauer@uni.lu

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For editorial correspondence, please contact:
martine.zenner@uni.lu

University of Luxembourg
Faculty of Law, Economics and Finance
Luxembourg School of Finance
4 Rue Albert Borschette
L-1246 Luxembourg

Recall Searching with and without Recall[‡]

Daniela Di Cagno*, Tibor Neugebauer**,
Carlos Rodriguez-Palmero*** & Abdolkarim Sadrieh****

* LUISS Guido Carli University of Rome
** University of Luxembourg, UJI Castellon, UCSB
*** University of Valladolid
**** University of Magdeburg

Forthcoming in Theory and Decision

Abstract

We revisit the sequential search problem by Hey (1987). In a 2x2 factorial design, varying fixed and random cost treatments with and without recall, we address open research questions that were originally stated by Hey (1987). Our results provide clear evidence for Hey's (1987) conjecture that recall negatively affects performance in sequential search. With experience, however, search behaviour with and without recall converges towards the optimal reservation rule. We further find that the utilization of optimal reservation rules is independent from the stochastic nature of the search cost.

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****Corresponding author**:
Tibor Neugebauer

University of Luxembourg
Luxembourg School of Finance (LSF)
4, rue Albert Borschette, L-1246 Luxembourg
+352 46 66 44 6285
tibor.neugebauer@uni.lu

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I. Introduction

In the nineteen-eighties, John Hey studied search problems both theoretically (Hey 1981a) and experimentally (Hey 1981b, 1982, 1987, 1991). He studied optimal reservation values and proposed rational solutions to sequential search problems with costly offers. In particular, Hey (1987) proposes several stopping rules to classify sequential search behaviour. The two most prevalent stopping rules he observes in his experiments are the (simple) *reservation Rule A*nd the *optimal reservation rule*. The (simple) *reservation* rule can be, but must not be, rational and specifies: "Stop buying offers if an offer is received that is 'sufficiently' high" (Hey 1987, p. 140). The term "sufficiently high" suggests that the rule requires that the searcher stops the search process as soon as the last received offer is at or above a given threshold value. Thus, the search process stops at the highest received offer, which presumably is the first received offer at or above the reservation value. The *optimal reservation rule* is the reservation rule that maximizes the searcher's expected payoff: "Stop buying offers if an offer is received that is greater than the optimal reservation value" (Hey 1987, p. 140).

Hey finds that most subjects' decisions are in line with a reservation rule – and many even in line with the optimal reservation rule –, if the underlying offer distribution is known and there is *no recall* (Hey 1987).[1] The fact that better information on the distribution of values improves decision-making seems straightforward. It is astonishing, however, that "the 'facility' of recall makes it less likely that the subject will follow a reservation Rule And less likely that the subject will follow an optimal reservation rule" (Hey 1987, p. 143). In other words, if subjects know that the best previous offer is available at any time during search,

[1] Note that in sequential search, the non-availability of the best past offer is usually called "no recall," even though the usual assumption is not that the decision-maker's memory is limited, but that past options are physically unavailable. In a classical example, a house seller receives independent offers for one available house, knowing that each offer to purchase can be accepted immediately, but will not be available later. A past offer can be accepted only if the seller is endowed with the facility to recall.

they are prone to continue their search for too long. While Hey (1987) provides graphical support for the *recall effect*, he reports no significant test results. In this paper, we report significant experimental results supporting Hey's (1987) conjecture on the recall effect. Furthermore, we address two other questions that Hey (1987, p. 143) raises, but leaves open for later research: (a) does the fraction of the population using the reservation rule increase over time? (b) Is the fraction of the population using the reservation rule lower if the search cost is stochastic?

We address these questions in a design with fixed versus random search cost and recall versus no recall. In all our treatments, we keep with the original design of Hey 1987, including the original sequence of rounds and the payoff and cost parameters. We were surprised to find no impact on the utilization of the reservation Rule And the optimal reservation rule when search costs were random. We do, however, find a strong negative effect of the recall facility on search performance. This result clearly supports Hey's (1987) conjecture. However, our results also show that search behaviour with and without recall converges towards the optimal reservation rule over time, with the subjects in the recall treatments reducing their search duration on average and the subjects in the no recall treatments increasing them. We find that this is good news for search theory.

The paper is organized as follows. In section 2 we briefly describe the experimental design, in section 3 we derive the testable hypothesis of optimal reservation value. Section 4 reports the results. In section 5, we reflect on the recall effect. In section 6, we discuss our results, comparing them to the literature and contemplating implications.

II. Experimental Design

We use a 2x2 factorial design for our experiment, in which we vary *fixed* versus *random cost* and *recall* versus *no recall* (see Table 1). The two *fixed cost* treatments α and β reproduce the full information treatments of Hey (1987). Subjects face a sequence of five search rounds (see Table 2). In each round, each subject receives an initial offer that is an independently drawn *offer*, a number drawn from a normal distribution with known parameter values and rounded to the next integer.[2] The subject decides whether to accept the offer or to ask for a new offer that is independently drawn from the same distribution.[3] Accepting an offer terminates the round. If the offer is not accepted, a new offer is drawn and presented to the subject as long as the total round length of three minutes is not reached. If the decision time is up before a subject has accepted an offer, the best (last) offer is automatically accepted in the recall (no recall) treatment.[4] Each offer, including the initial offer, comes at a cost. The cost of receiving a new offer is always constant within each round in the fixed cost treatment. Following Hey (1982) the cost in round 1 is 100, in round 2 it is 50, in round 3 it is 10, in round 4 it is 20, and in round 5 it is 100 again. In the random cost treatments, the cost of receiving a new offer is independently drawn with equal probability from the set {10, 20, 50, 100} in all rounds and for each new offer. The payoff from the search in any given round is calculated as the accepted offer minus the accumulated cost of search in that round. In the *recall* treatments, the accepted offer is the highest offer received in the round. In the *no recall* treatments, the accepted offer is the last offer received.

[2] While we draw all values from the normal distributions as described in the instructions, we follow Hey (1982) and report zeros for any negative value drawn and 3000 for any value drawn above 3000. Setting all negative draws to zero does not affect the optimal search policy, which is based on the upper order statistics of the distribution, because negative offers should be rejected in any case. Setting all values above 3000 equal to 3000 theoretically has only a small impact on the optimal policy. Since the probability of these events is extremely small, the impact of our manipulation is too small to actually affect the optimal reservation price at any practical precision. We never observe a draw at or above 3000 in the experiment. As Hey (1982, 1987) notes, the lower bound at zero protects subjects from very costly mistakes and the higher bound protects the experimenter from making very high subject payments. But, neither bound has a practical impact on optimal decisions.

[3] At the start of each round, subjects familiarize themselves with the normal distributions whose parameters are revealed to them by repeatedly drawing offer and cost realizations from the corresponding distributions. These “trials” have no financial consequences and subjects were perfectly aware that they were independent from the actual experimental offers. In the design and analysis of our study we follow the original presentation of Hey (1987), including the procedure with computerized draws and an experience phase. A careful reviewer suggested that the use of a bingo cage or other simple randomization devices would possibly promote a better understanding among subjects than this procedure. In fact, we do not know of any evidence showing that the use of a mechanical device has a significant impact on observed behaviour. We call for future research to study this methodological issue which we think is worth of attention as the reviewer has noted.

[4] Note that we only observed a single instance in the entire experiment, in which a round was terminated for a subject, because the three minutes limit was reached. This was the first round of a subject that exhibited average behaviour in all other rounds. It remains unclear, whether the subject was simply confused or not.

After the experiment, a die roll randomly selected the round of the experiment that determined the subject's payoff. The experimental earnings were exchanged at a rate of 40 points to 1 Euro. No show-up fee was offered. The experiment took about half an hour and subjects earned an average of 14.30 Euro. The experimental design including cost parameters and distributions were prior knowledge to subjects and displayed on their screen. The experimental sessions generated 4 (treatments) x 14 (subjects) independent observations.

Table 1. The four treatments

	Recall	no recall
fixed cost	α	β
random cost	α'	β'

The experiment was conducted at the MaXLab of the University of Magdeburg. We used zTree (Fischbacher 2007) for the software, and ORSEE (Greiner 2004) for the recruitment. Subjects were given written instructions that were read aloud (see appendix). Questions were answered individually in the cubicles. Subjects had not participated in a search experiment before and were unfamiliar with search problems.

III. Optimal reservation value

The optimal reservation value R as derived in Hey (1981a) under the assumptions of an indefinite horizon, risk neutrality, and no discounting is given by

$$\int_R^\infty [1 - F(x)]\,dx = c \tag{1}$$

where $F(\cdot)$ is the distribution function of the offers and c is the *expected* offer cost. Using integration by parts and the standard normalization, we arrive at (see appendix for the proof):

$$(\mu - R) \cdot \Phi(\frac{\mu - R}{\sigma}) + \frac{\sigma}{\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{\mu - R}{\sigma}\right)^2} = c \qquad (2)$$

when $F(x)$ is the distribution function and $f(x)$ is the density function of the standard normal distribution.

Given the parameters used in the treatments (see Table 2), we compute the optimal reservation value for each round in each treatment.[5] The strategy that maximizes the expected payoff is to accept any offer above and to reject any offer below the optimal reservation value. This feature of the decision situation is independent from the recall facility. Following the literature (e.g. Hey 1982, Hey 1987, Cox and Oaxaca 1996), our optimal reservation value benchmarks are based on risk neutral preferences. Hence, the benchmarks for the random cost treatments are calculated using the expected value of the cost, i.e. 45 points. These risk neutral benchmarks are informative, because they draw a division line between risk-averse search behaviour (reservation values below the benchmark) and risk-seeking search behaviour (reservations values above the benchmark).

IV. Experimental Results

Table 3 displays summary statistics of the data on treatment level and overall.[6] The great majority of our observations (85%) are in line with one of the two reservation rules (A or A*) proposed in Hey (1987, p. 140) which we repeat hereafter:[7]

"Rule A. ('Reservation' rule.) Stop buying offers if an offer is received that is 'sufficiently' high."

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[5] The table gives the exact reservation values up to the decimal.

[6] Appendix A contains a summary of our experimental results at the level of individual subjects.

[7] The observed behavior is in line with Rule A* if and only if the searcher stops searching upon receiving the first offer that exceeds the optimal reservation value. In contrast, the observed behavior is in line with Rule A, if indeed the searcher stops searching upon receiving the highest offer in the sequence but that that offer is (1) either not the first offer to exceed the optimal reservation value or (2) that offer, despite being the highest one, does not exceed the optimal reservation value. Rule A is thus based on the assumption that the searcher has indeed an unobservable reservation value different from the optimal one.

Rule A*. (‘Optimal Reservation’ rule.) Stop buying offers if an offer is received that is greater than the optimal reservation value.”

Overall 55% are in line with the optimal reservation Rule A*, while 30% are in line with the simple reservation Rule A.[8] Only a very small fraction of the remaining observations is in line with the other rules that Hey (1987) suggested. Only 6% are of the types B, C, D, or E, while the other 9% are not in line with any of the rules.[9]

Table 2. Parameters in the five rounds of the experiment

round	mean offer μ	standard deviation‡ σ	fixed cost c	optimal reservation value R	random cost c'	optimal reservation value R'
1	600	250	100	599.5	{10,20,50,100}	739.9
2	475	250	50	598.2	{10,20,50,100}	614.9
3	510	200	10	761.1	{10,20,50,100}	593.1
4	420	200	20	600.5	{10,20,50,100}	503.3
5	350	500	100	596.4	{10,20,50,100}	829.9

‡Note: In line with Hey (1987), the offer distributions were truncated at 0 and 3000 points.

Table 3. Summary statistics on treatment level

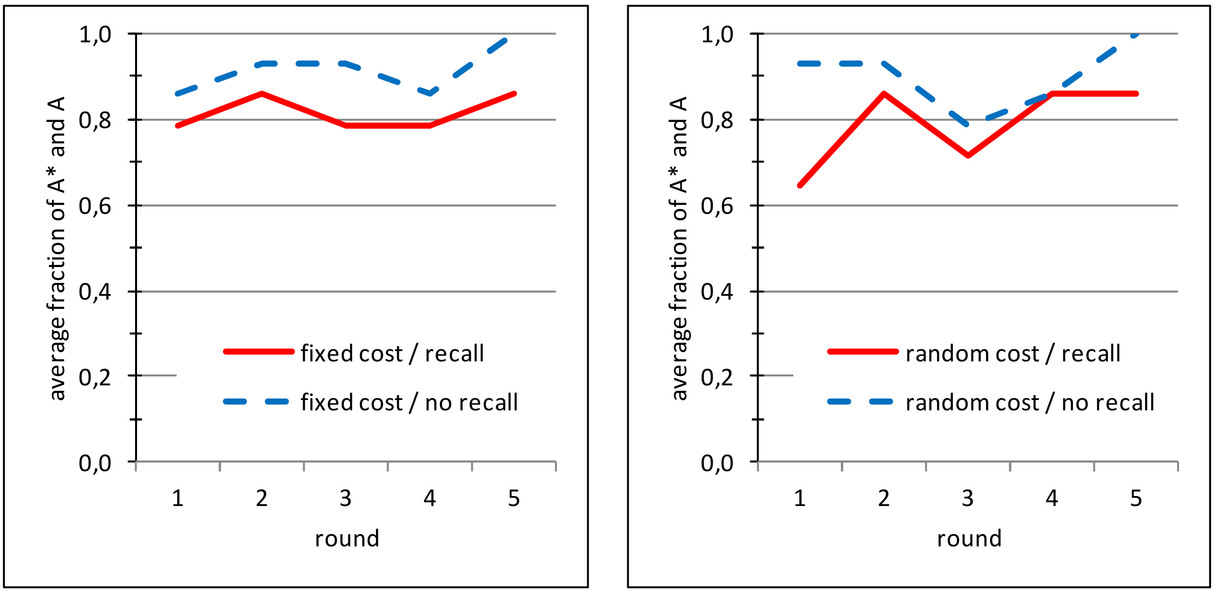
treatment	recall	cost type	relative frequency of rule							avg. number of requested offers	
			A*	A	B	C	D	E	None	all rules	only A*+A
α	yes	Fixed	0.51	0.30	0.00	0.04	0.00	0.06	0.09	5.61	4.17
β	no	Fixed	0.57	0.34	0.00	0.00	0.00	0.03	0.06	4.23	3.12
α'	yes	Random	0.51	0.27	0.03	0.04	0.00	0.00	0.14	5.61	3.47
β'	no	Random	0.60	0.30	0.01	0.00	0.00	0.03	0.06	3.46	2.72
Overall			0.55	0.30	0.01	0.02	0.00	0.03	0.09	4.73	3.36

[8] The average accepted offer under Rule A is 105% (36%) of the optimal reservation value (standard deviation in parenthesis), and almost all accepted offers under Rule A are at or above 66% of the optimal reservation value.

[9] Hey (1987) calls these rules “irrational” either because they imbue the order of the offers with some significance (B and C) or because they ignore the cost of buying offers. Hey (1987) defines the rules as follows: Rule B (“One bounce”): “Buy at least 2 offers; stop if an offer is received less than the previous offer.” Rule C (“Two bounce”): “Buy at least 3 offers; stop if both the last offer and the next to the last are smaller than the second to the last.” Rule D (“Modified one bounce”): “Buy at least 2 offers; stop if an offer is received less than the previous offer plus the offer cost.” Rule E (“Modified two bounce”): “Buy at least 3 offers; stop if both the last offer is less than the second to last plus twice the offer cost and the next to last is less than the second to last plus the offer cost.”

As shown in Figure 1, the fraction of reservation rules (A* and A) actually even increases slightly over time, reaching 100% in the last round of the two treatments without recall. The two panels in Figure 1 also seem to suggest that the number of subjects using one of the reservation rules is generally greater in the treatments without recall than in those with recall.

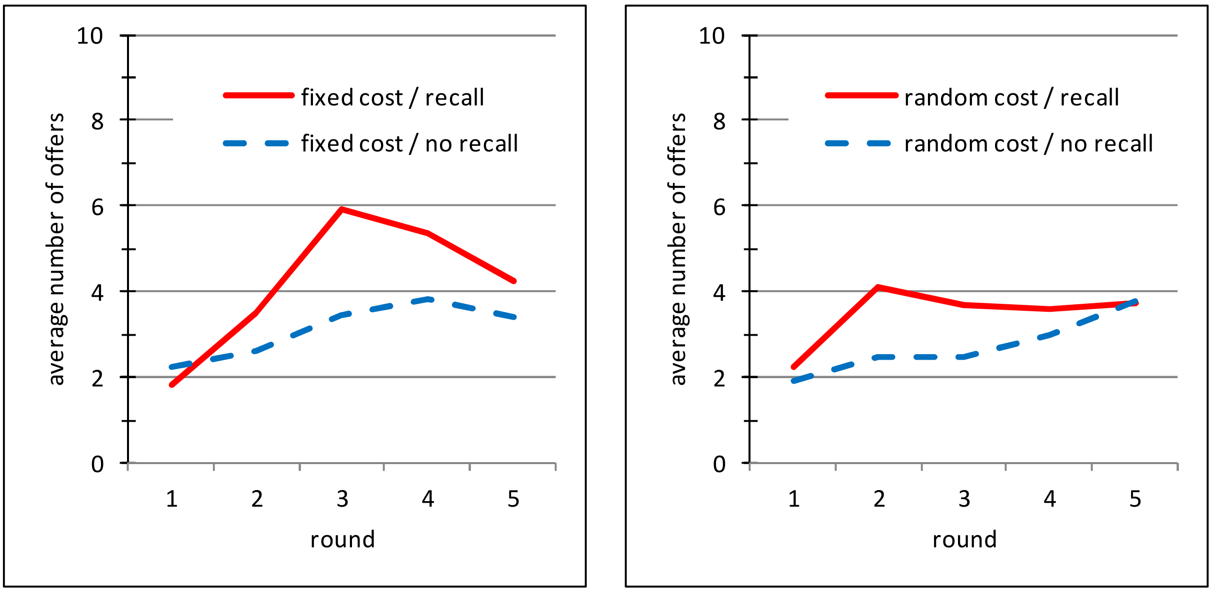
Figure 1. Development of the utilization of the (optimal) reservation rules A* and A



A second look at the last two columns in Table 3 confirms that the recall facility not only affects the usage of the reservation rules, but also increases the duration of search. No matter whether we count the number of requested offers by all subjects (one-to-last column) or only the requests by the subjects using the two reservation rules (last column), we always find that the average number of requested offers is larger in the treatments with than without recall. This finding is supported by the graphs in Figure 2 that show the development of the average number of offers requested by the subjects using reservation rules. In both panels (fixed cost on the left and random cost on the right), the solid line representing the treatments with recall lies above the dashed line that represents the treatments without recall almost everywhere.

Figure 2 also shows that the request frequencies in all four treatments tend to converge towards the end of the experiment. While we find that the frequency of offer requests is higher in the treatments with recall (see above), this difference is no longer significant in the last round. It seems that subjects are not only learning to use the reservation rules more frequently towards the end of the experiment, but they are also learning to use the recall facility more rationally.

Figure 2. Development of the average number of offers requested by A* and A subjects



We finalize our analysis of the data with two regressions that confirm our descriptive findings so far. Table 4 reports the results of a probit regression with random effects, in which we regress the probability of using one of the reservation rules (A* or A) on the two treatment dummies (RECALL and RANDOM), the round number t, and the expected offer cost c_{it}. To control for the fact that we have a panel (i.e. multiple responses from subjects), we use the following random effects version of the probit model:

$$\Pr(search\ rule_{it} = A \vee A^*) = \Pr(b_0 + b_1 RECALL_i + b_2 RANDOM_i + b_3 t + b_4 c_{it} + u_i + v_{it} > 0)$$

where $RECALL_i = 1\ for\ \beta, \beta'$, $RANDOM_i = 1, for\ \alpha', \beta'$ and 0 otherwise,

$$u_i \sim N(0, \sigma_u^2), v_{it} \sim N(0,1) \cdot \qquad (3)$$

The significantly negative coefficient of *RECALL* in Table 4 underlines our finding that the probability of using one of the reservation rules is lower with recall facility than without. Hence, we provide the first statistical evidence on the conjecture that Hey (1987) had made concerning the negative effect of the recall facility on search performance. Obviously, no significant effect can be found for *RANDOM*, i.e. the choice of the search rule is not influenced by the question whether the cost of search is random or fixed. The positive coefficient on the time trend indicates that there is no decreasing usage of reservation rule between rounds. Since the coefficient barely fails weak significance, we conjecture that there probably is a positive trend to increase the usage of the reservation rules with experience, even though our statistics here are not picking it up.

Table 4. Probit regression of A or A* rule choices with random effects

Variable	coefficient	std. error	Z	p-value
Constant	1.1672	0.4370	2.67	0.008
RECALL	-0.6005	0.2964	-2.03	0.043
RANDOM	-0.0893	0.2888	-0.31	0.757
round *t*	0.1212	0.0778	1.56	0.119
expected cost *c*	0.0028	0.0040	0.70	0.482
log likelihood = -108.2 , # obs. = 280, # subjects = 56, # obs. / subjects = 5				

In the probit regression above, we do not observe an effect of the size of the offer cost on the choice of the decision rule. This is in line with rational behaviour that prescribes using a reservation rule no matter what the cost of requesting an offer is. As can easily be seen from equations (1)-(2), however, the optimal reservation value decreases with increasing costs. The cost parameter, thus, should affect the number of requested offers negatively. This is exactly what we find in the Poisson regressions presented in Table 5 and Table 6, below. We analyze the effect of the cost, the treatment parameters, and the subjects' experience (i.e. the round number) on the number of requested offers in Poisson regressions, because the requests – by design – must be greater or equal to 1 and are distributed with a left skew. Both estimated models allow random effects to deal with the panel structure of our data and are based on the following equation, where we replace the round number *t* that is used in the first regression (see Table 5) with an interaction effect of the round number and the *RECALL* dummy for the second regression (see Table 6):

$$\ln(requested_{it}) = b_0 + b_1 RECALL_i + b_2 RANDOM_i + b_3 t + b_4 c_{it} + u_i + v_{it}$$

where $RECALL_i = 1 \; for \; \beta, \beta'$, $RANDOM_i = 1, for \; \alpha', \beta'$ and 0 otherwise,

$$u_i \sim \Gamma(k, \theta_u), v_{it} \sim \Gamma(k, \theta_v) \,. \qquad (4)$$

As predicted and as mentioned above, the cost parameter has a strong and significantly negative effect on the number of requested offers in both regressions. The more surprising finding is that the number of requested offers is not affected by the riskiness of the cost (treatment dummy *RANDOM*). This is remarkable, because a number of other studies show that risk- or loss-aversion may affect search behaviour (Cox and Oaxaca 1989; Sonnemans 1999; Cox and Oaxaca 2000, Bonne, Sadrieh, van Ours 2009; Schunk and Winter 2009). The other treatment dummy, *RECALL*, has a strong and significantly positive effect on the number of requested offers in both regressions. This is in line with the result of our non-parametric tests, showing that the recall facility not only affects the choice of the search rule, but also the duration of search. This is also in line with the literature on search settings with a limited number of offers, in which the recall facility leads to a larger number of requested offers, but does not interact with risk aversion in the predicted manner (Cox and Oaxaca 1996).

Table 5. Poisson regression of requested offers with random effects

Variable	Coefficient	std. error	z	p-value
Constant	1.7120	0.1503	11.39	0.000
RECALL	0.3833	0.1454	2.64	0.008
RANDOM	-0.1360	0.1454	-0.94	0.350
round t	-0.0162	0.0204	-0.80	0.426
expected cost c	-0.0052	0.0010	-5.04	0.000
log likelihood = -923.3 , # obs. = 280, # subjects = 56, # obs. / subjects = 5				

Finally, checking for the effect of experience on the number of offers requested, we have included the round number in the regression presented in Table 5, but find that the estimated coefficient is not significant. This seems related to the opposite tendencies that the graphs in Figure 2 show, where the number of requested offers in the treatments without recall seem to increase over time, while those in the treatments with recall seem to decrease. To check for a treatment time interaction effect, we ran the regression displayed in Table 6. Indeed, we find a significantly negative interaction effect, clearly indicating that the number of requested offers in the treatments with and without recall converge over time.[10] We conjecture that the subjects in the treatments without recall learn to be less anxious in requesting offers, while those in the recall treatments learn to be more vigilant.

V. Reflections on the Recall Effect

We find empirical evidence that subjects in all treatments of our search experiment in general follow a reservation rule. However, the data also show that subjects tend to search longer if they are endowed with the facility to recall. These findings are perfectly in line with

[10] Note that this interaction effect seems to be robust and independent, because including the interaction term instead of the round number variable leaves the size and the sign of all other estimated coefficients basically unaffected.

the results reported by John Hey (1987, 1991). In his original study, John Hey (1987, p. 138) refers to the tendency of subjects to exhibit longer search duration as the "effect of removing the 'recall' option." The recall effect is a violation of the optimal reservation rule determined in equations (1)-(2), since optimal search prescribes stopping search immediately at the arrival of an offer that is at or above the reservation value. Under the optimal reservation rule, accordingly, search behaviour should be unaffected by the recall option.[11] The convergence of the number of requested offers in the treatments with and without recall indicates that the recall effect diminishes over time, but the question why the recall effect emerges in the first place still begs an answer.

Table 6. Poisson regression of requested offers with random effects and interaction

Variable	coefficient	std. error	z	p-value
Constant	1.6685	0.1346	12.40	0.000
RECALL	0.5429	0.1647	3.30	0.001
RANDOM	-0.1370	0.1454	-0.94	0.346
$t \times RECALL$	-0.0538	0.0265	-2.03	0.042
expected cost *c*	-0.0053	0.0010	-5.14	0.000
log likelihood = -921.6 , # obs. = 280, # subjects = 56, # obs. / subjects = 5				

In this section, we provide possible theoretical approaches to explain the emergence of the recall effect. Since all approaches are feasible, but rather demanding in terms of the modelling technology needed, we restrict our discussion here to a brief account of the intuition underlying each of them.

[11] In their search setting with a limited number of offers, Cox and Oaxaca (1996) also find that recall increases search duration. This increase in the number of requested offers, however, is smaller than expected with risk neutral preferences, indicating that subjects seem more risk averse in the recall than in the no recall treatment, even though the outcome risk is smaller in the former than in the latter. They conjecture that the recall option affects search behaviour in ways that go beyond (or even contradict) the usual effects of risk preferences. We only find the recall effect, but no effect of the risk preferences.

One possible explanation for the existence of the "recall effect" is risk aversion. In general risk aversion should lead to a shorter search with a lower reservation value. However, as John Hey (1981, p. 74) points out the recall effect applies to the finite horizon model only. "Clearly in the infinite-horizon model, the question of recall is of no consequence, since the reservation value is constant; an unacceptable offer is always unacceptable. In the finite-horizon model, however, this is not the case, since the reservation value falls as the horizon approaches. [Then] the question of recall is crucial." In the finite horizon, hence, the expected utility in the situation without recall is lower than with recall because recalling the highest offer substantially reduces the risk. However, even in the setting with a limited number of offers, Cox and Oaxaca (1996) conclude that no theoretically consistent risk aversion model can predict subjects' behaviour both with and without recall.

Another possible approach to explain the recall effect is based on the disappointment theory (Gul 1991).[12] According to this approach, when evaluating the utility of random prizes individuals experience elation, whenever the prizes are better than the certainty equivalent of the lottery they imply, but experience disappointment, whenever the prizes are worse than that certainty equivalent. The elation effect in sequential search is not affected by recall, because elation is related to a new offer that is better than expected and can be accepted in both conditions. In contrast, the recall option affects the extent of disappointment strongly. Subjects are disappointed when the offer that they can accept is worse than expected. With recall, the offer that can be accepted is the maximum offer ever received, while without recall it is always only the newest offer. Clearly, the expected maximum value of any given number of draws from a stochastic distribution is never smaller and will usually be strictly greater than the most recent draw. Hence, disappointment is usually smaller and never greater with recall than without. Since the disappointment asymmetry is not balanced by an elation

[12] We are indebted to Glenn Harrison for suggesting this approach at the Durham Workshop 2013 that was held in honour of John Hey. Note that our discussion also holds for other decision models based on disappointment, e.g. Loomes and Sugden (1986).

asymmetry across conditions, the expected net value of requesting the next offer is greater with recall than without, leading to longer optimal search duration.[13]

A different theoretical approach to explain the recall effect was suggested by John Hey.[14] This approach is based on the wealth effect of the accumulated cost of search within an expected utility framework that restricts the domain of wealth to the current decision situation, i.e. to the experiment.[15] In such a setting, the accumulated cost of search reduces the searcher's wealth, which is bounded from above at 3000 in our experiment. Taking account of this bound, the accumulation of offer costs converts the problem to one of a limited number of draws. As pointed out above, the question of recall is crucial in the finite horizon scenario.

The outlined approaches provide rather intuitive theoretical explanations for the recall effect. While the risk aversion explanation is based on the lower variance of outcomes with than without recall, the disappointment and the accumulated cost approach make use of the larger loss potential that rejecting an offer has when the recall option is absent. None of the approaches, however, can accommodate the fact that the observed recall effect disappears as subjects gain experience in our experiment. Our data suggest that with experience (i.e. by repeatedly playing the game) subjects learn to adapt their reservation value to the optimal reservation value in both conditions, with and without recall. Interestingly, the subjects in the condition without a recall option start from an under-estimation of the optimal reservation value, while those in the recall treatment start from an over-estimation. Hence, the recall effect may simply be a perception effect, inducing an exaggerated fear of losses in subjects without a recall option and an exaggerated optimism in the subjects with a recall option. The

[13] A formal proof of the argument can be obtained from the authors upon request.
[14] We are indebted to John Hey for suggesting this approach in a private communication after the presentation of our results at the Durham Workshop 2013 that was held in his honor. The approach is related to his formal discussion in Hey (1981, pp. 69-75).
[15] See Cox and Sadiraj (2006) for a discussion of how and why the wealth domain in expected utility models may be restricted.

recall effect disappears with experience, because subjects in both treatments learn to adapt their reservation value rules in the direction of the optimal reservation value rule.

VI. Discussion and Conclusion

Relating to some of John Hey's pioneering work (1981a, 1981b, 1982, 1987, and 1991), we conduct a sequential search experiment, in which subjects can request an unlimited number of costly offers that are random draws from a known distribution. Our innovation is to introduce two treatments, in which the cost of acquiring an offer is stochastic and randomly drawn from a known distribution only after the subject has decided to acquire a new offer. We find that both the utilization of the reservation Rule And the optimal reservation Rule Are not statistically different in the two cases. In both cases, following a reservation rule, subjects request new offers as long as these remain below a critical value and immediately accept the first offer that is greater than the reservation value. The reservation rule defines rational behaviour both with and without recall, i.e. with or without a permanent availability of the best encountered offer.

We follow Hey (1987) by labelling the reservation rule that is optimal for a risk neutral individual as A* and labelling all other reservation rules as A.[16] We find that about 85% of the search behaviour observed in our experiment is in line with one of the two reservation rules. Supporting some of the conjectures of Hey (1987), we find that

(a) Recall makes the utilization of a reservation rule significantly less likely.

(b) Recall has a significant positive effect on the number of requested offers.

(c) While the utilization of reservation rules is not significantly affected by experience, the number of requested offers converges with experience, decreasing in the treatments with recall and increasing in those without recall.

[16] In our data we found a very low prevalence of the other possible search rules suggested by Hey (1987). We, therefore, focus our analysis only on the extent and dynamics of the usage of the reservation rules.

(d) Fixed or random costs make no difference for the use of a reservation rule.

Our study contributes in a number of ways to the literature on search behaviour. First, we introduce risk in the offer cost parameter to find that such an introduction neither affects the theoretical risk neutral prescription to utilize reservation rules for sequential search, nor the behaviour of subjects in such settings.

Second, we provide strong evidence for John Hey's conjecture that the recall facility seriously hampers the decision-makers' capability to make rational choices in sequential search (Hey 1987). Interestingly, however, it seems that the negative effect of recall (i.e. of the permanent availability of the best previous offer) decreases over time as subjects learn to request less offers over time when they are endowed with the recall option. We conjecture that subjects do worse with recall, because the absent risk of losing a "good" offer encourages subjects to request more offers than they optimally should. Hence, inexperienced subjects with a recall option lose money when compared to those without the option, because their willingness to spend on offers is higher due to the smaller risk of regret. Previous studies (e.g. Braunstein and Schotter 1982 and Kogut 1992) had detected a substantial number of instances of using the recall option, but could not observe the detrimental effect of recall that we observe, because they did not compare the search performance to the case without recall.

Cox and Oaxaca (1996) report the only other study (that we are aware of) in which behaviour in a no recall and a perfect recall sequential search setting are directly compared. In contrast to most other studies – including Hey (1982 and 1987) and our study –, the number of available offers in the Cox and Oaxaca (1996) setting is strictly limited and known. This slightly changes the optimization logic of the decision and leads to different optimal stopping benchmarks, where the optimal number of requested offers is smaller without than with recall. Comparing the observed number of requested offers to the risk neutral benchmark of the corresponding treatment, Cox and Oaxaca (1996) find a greater distance to optimality in the treatment with recall than without recall. While in a different setting, this result is in line with our observation that the recall option may seriously harm sequential search outcomes.

Interestingly, the greater distance from the risk neutral benchmark that Cox and Oaxaca (1996) observe in the treatment with perfect recall, also rules out risk aversion as a simple explanation of the observed sequential search behaviour. Cox and Oaxaca (1996) conclude their study explaining that "subjects search as if they are more risk averse in the presence of perfect recall" even though "perfect recall decreases the riskiness of the wage offer distribution." This, they conclude, means that "the general concave model also fails to predict how subjects will respond to the introduction of perfect recall opportunities." (Cox an Oaxaca 1996, p. 195)

While our setting is strictly sequential as in most of the early experimental studies of search behaviour (Rapaport and Tversky 1970; Hey 1982; Braunstein and Schotter 1982; Hey 1987: Kogut 1990), our main result is also informative for mixed settings that were studied later. Harrison and Morgen (1990), for example, study a search setting, in which the decision-maker can choose to request multiple offers in an otherwise sequential setting without recall. Their surprising finding is that subjects do not manage to reap the theoretically predicted higher profits from using the option to request more than one offer in the multi-offer treatment. Our findings may shed some light on this counterintuitive result. Having multiple offers at hand creates a situation that is similar to having the possibility to recall and our study shows that the option to recall induces subjects to search longer than theoretically optimal.[17]

All in all, our results support and extend the results by Hey (1982 and 1987). Search behaviour is hardly affected by stochastic search cost, but may be hampered by a recall

[17] A recall effect may also be driving some of the sub-optimal results observed by Caplin, Dean, and Martin (2011), who study choices from large lists of items that are presented simultaneously, but need an essentially sequential evaluation, i.e. their setup entails recall and a cognitive cost of item evaluation, but no exogenously given sequence and no monetary search cost.

facility. With experience, however, we observe that searchers adapt well to the search environment, utilizing almost optimal stopping rules for most parts.

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Online Appendix A – Summary of the results of the experiment

treatment	average		Number of offers in round				Behavior consistent with rule in round‡				
subject	# trials	1	2	3	4	5	1	2	3	4	5
α1	12	6	1	1	1	1	E	A	A	A	A*
α2	14	2	5	5	12	11	A*	A*	A*	A	E
α3	20	30	1	2	22	8		A*	A*	C	A*
α4	7	1	3	3	5	10	A*	A	A*	A*	A
α5	29	1	2	10	6	2	A*	A*			A*
α6	4	1	5	8	1	3	A*	A	A	A	A*
α7	22	3	9	35	3	2	A	A	E	A	A*
α8	8	1	4	2	4	2	A*	A*	A	A*	A*
α9	23	1	2	20	9	1	A*	A*	A	A*	A*
α10	11	4	4	5	6	4	E		A*	A*	C
α11	13	3	6	8	9	8	A	A	A*	A*	A
α12	7	2	3	10	11	7	A	C			A
α13	14	4	1	4	8	5	A*	A*	A*	A*	A*
α14	16	1	3	7	1	2	A*	A*	A	A	A*
β1	11	1	1	7	8	2	A*	A*	A	A	A*
β2	11	1	1	2	3	8	A	A*	A*	A*	A*
β3	13	3	2	3	3	4	A	A*	A	A*	A*
β4	25	1	1	11	8	6	A	A*	A	A*	A*
β5	9	1	10	3	9	1	A	E	A		A*
β6	17	2	1	4	1	2	A*	A	A*	A*	A
β7	13	6	5	2	7	1		A*	A*		A*
β8	17	1	5	2	3	1	A	A	A*	A*	A*
β9	17	1	1	2	6	2	A	A*	A*	A*	A
β10	24	1	1	2	2	1	A*	A	A*	A*	A
β11	26	2	11	34	5	7	A*	A		A*	A
β12	23	30	1	3	2	1	E	A	A*	A*	A
β13	16	4	1	1	1	6	A	A*	A*	A*	A*
β14	13	9	3	3	4	6	A*	A	A*	A	A*
α'1	8	2	4	35	2	6	B	A*	C	B	C
α'2	10	8	14	1	11	7	C	A	A*		
α'3	10	5	6	6	1	6	A*		A*	A*	A
α'4	12	1	1	14	4	7	A*	A	A	A*	A*
α'5	13	3	34	4	11	10	A*		A*	A	A
α'6	15	2	5	4	6	3	A	A		A	A*
α'7	25	23	3	1	2	1		A*	A*	A*	A*
α'8	25	6	4	3	5	2		A*		A	A
α'9	12	1	1	7	4	3	A*	A*	A	A*	A*
α'10	16	45	5	1	4	4		A*	A*	A*	A*
α'11	13	2	7	1	3	2	A*	A	A*	A	A*
α'12	17	1	1	7	1	2	A	A*		A*	A*
α'13	7	1	3	1	1	4	A	A*	A*	A	A
α'14	15	4	1	1	1	1	A	A*	A*	A*	A*
β'1	15	3	4	4	5	4	A*	A*	A	A*	A*
β'2	27	1	1	1	1	4	A*	A	A*	A	A
β'3	37	3	2	2	1	2	A*	A*	A*	A*	A
β'4	13	1	2	1	3	1	A*	A	A*	A	A*
β'5	19	5	6	8	19	8	A*	A*		E	A*
β'6	6	2	18	9	2	1	A	E		A*	A
β'7	14	3	3	1	1	2	A*	A*	A*	A*	A*
β'8	14	1	4	1	7	2	A*	A	A*	A	A
β'9	10	1	1	10	2	6	A	A		A*	A*
β'10	19	2	1	6	1	4	A*	A*	A*	A	A
β'11	15	2	2	2	3	1	B	A	A		A*
β'12	12	1	1	3	5	7	A*	A*	A*	A*	A*
β'13	8	1	1	4	6	1	A*	A*	A*	A	A
β'14	19	1	4	2	2	10	A*	A*	A*	A*	A

‡Note: (Optimal) Reservation Rule A (A*), (D, E) B, C (Modified) One, Two Bounce rule respectively. The first column shows the treatment codes and the subjects' identification numbers. The second column shows the average number of trial draws that each subject took from the distribution, before making his or her decision. Columns 3-7 show the number of costly offers each subject requested. Finally, columns 8-12 display the type of search rule that – according to the classification in Hey (1987) – fits best to the observed behavior of each subject and in each round.

Appendix B – Proof

We present the search problem by making use of a standard-normal distribution function,

$$\Phi(z) = P(N_{(0,1)} \leq z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = \int_{-\infty}^{z} f(x)dx$$

where $\Phi(z)$ is the cumulative probability that the realization of a normally distributed random variable $N_{(0,1)}$ with zero expected value and unit standard deviation is smaller or equal to a real number z .

Starting from the solution to the general search problem involving an arbitrary cumulative probability distribution $F(x)$ as described in equation (1) and in Hey (1981), we make the following algebraic operations given the underlying normal distribution with mean μ and standard deviation σ .

$$c = \int_{R}^{\infty} (1 - F(x))dx$$

$$= \int_{R}^{\infty} \left(1 - P\left(N_{(\mu,()} \leq x\right)\right)dx$$

$$= \int_{R}^{\infty} \left(1 - \Phi\left(\frac{x-\mu}{\sigma}\right)\right)dx$$

$$= \int_{R}^{\infty} \Phi\left(\frac{\mu - x}{\sigma}\right)dx$$

$$= \int_{R}^{\infty} \int_{-\infty}^{\frac{\mu-x}{\sigma}} f(y)dy\,dx$$

Changing the order of integration yields

$$= \int_{-\infty}^{\frac{\mu-R}{\sigma}} \int_{R}^{\mu-\sigma y} f(y)dx\,dy$$

$$= \int_{-\infty}^{\frac{\mu-R}{\sigma}} (\mu - \sigma y - R)\, f(y)dy$$

$$= (\mu - R)\,\Phi\left(\frac{\mu - R}{\sigma}\right) - \sigma \int_{-\infty}^{\frac{\mu-R}{\sigma}} y\, f(y)dy$$

$$= (\mu - R)\,\Phi\left(\frac{\mu - R}{\sigma}\right) - \sigma \int_{-\infty}^{\frac{\mu-R}{\sigma}} y \cdot \frac{1}{\sqrt{2\pi}} \mathrm{e}^{-\frac{1}{2}y^2} dy$$

From the fact that $(-f(y))$ is an antiderivative of $(y \cdot f(y))$, we have

$$c = (\mu - R)\,\Phi\left(\frac{\mu - R}{\sigma}\right) - \sigma\left(-\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}y^2}\right)\Big|_{-\infty}^{\frac{\mu-R}{\sigma}}$$

Which yields the desired equation (2) as an outcome.

$$c = (\mu - R)\,\Phi\left(\frac{\mu - R}{\sigma}\right) + \frac{\sigma}{\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{\mu-R}{\sigma}\right)^2}$$

$c = \sigma(x \cdot \Phi(x) + f(x))$, where $x = \left(\frac{\mu - R}{\sigma}\right)$

q.e.d.

For instance, for given $c = 1,\quad \mu = 6,\quad \sigma = 2.5$ as in the first treatment, we can implicitly determine the optimal reservation value, R ,

$$1 = (6 - R)\,\Phi\left(\frac{6 - R}{2.5}\right) + \frac{2.5}{\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{6-R}{2.5}\right)^2},$$

for which numerical approximation yields $R = 5.99$ as recorded in the first row to Table II.

Appendix C – Instructions

You are participating in an economics experiment, in which you can earn money that will be paid to you in cash. Your payoff will depend on your own choices and on chance moves.

The Experiment

The experiment involves 5 rounds.

In each of the 5 rounds you will collect points depending on your choice and on chance.

At the end of the experiment, one of the 5 rounds will be determined randomly and the points of that round will be paid out to you in cash with an exchange rate of 40 points = 1 Euro.

Offers

In each round you will first see an initial offer.

If you like the initial offer, you can accept it immediately.

If you do not like the initial offer, you can request to see further offers. For each offer, you will have to decide whether to accept it or not.

All offers are independently and randomly drawn from a normal distribution (bell-shaped distribution). The mean and standard deviation of the distribution of the offers remain the same during a round, but change from round to round. The parameter values of the current round are displayed on the screen.

Accepting an offer and the round termination

[*No Recall*: You can always only accept the last offer drawn. If you do not accept the current offer immediately, it will not be available later.] [*Recall*: You can decide whether to accept the best offer drawn so far. If you do not accept the offer immediately, it will stay an available option until a better offer is drawn.]

Accepting an offer terminates the round.

If the decision time (3 minutes) is up before you have accepted an offer, the [*No Recall*: last] [*Recall*: best] offer is automatically accepted and the round ends.

Cost of offers and score

Each offer that you are shown incurs a cost.

Your points for the round are equal to the offered points minus the accumulated cost of offers. This score, which is decisive for your payoff, is displayed as "net offer" on your screen.

The cost of an offer is 10, 20, 50, or 100. [*Fixed cost*: The cost of an offer is fixed within a round, but varies from round to round. The relevant cost is displayed on your screen.] [*Random cost*: The offer cost is independently drawn for each individual offer, where each of the four values may be drawn with equal probability. At the time you make your decision, you only know the distribution of possible offer costs, but not the actual offer cost that applies to the next offer.]

As long as the cost of offers you accumulate in one round does not pass 3000 points, you can request to see new offers.

Trial phase

Before the start of each round, you can use the trial phase to request an arbitrary number of test draws from the distribution of offers and cost to be shown on the left side of the screen.

In contrast to the draws of the actual offers, the trials incur no cost and cannot be accepted. They only help to give you an impression of the distribution of offers.