Experimental Economics, 2:197–225 (2000)

Good News and Bad News: Search from Unknown Wage Offer Distributions

JAMES C. COX
Department of Economics and Economic Science Laboratory, University of Arizona, Tucson, AZ 85721-0108
email: jcox@bpa.arizona.edu

RONALD L. OAXACA
Department of Economics, University of Arizona, Tucson, AZ 85721-0108
email: rlo@u.arizona.edu

Abstract

The largest market in national economies is the labor market. Labor market contracting is characterized by job search, often from unknown wage offer distributions. This paper reports experimental tests of finite horizon models of job search in which the wage offer distribution is unknown. Theoretically-optimal search from an unknown wage offer distribution can have the seemingly paradoxical property that some offers will be accepted that are lower than other offers that will be rejected in the same period of the search horizon. Thus the reservation wage property (or lowest acceptable wage path) may not exist. This can occur because an offer that is a priori relatively high ("good news") can imply that it is highly probable that search is from a favorable distribution, and such an offer can look unattractive when it is an a posteriori relatively low offer from a favorable distribution ("bad news"). This paper reports results from experimental treatments for search from unknown distributions in which the reservation wage property does exist and treatments in which it does not exist. We find that the consistency of search behavior with search theory reported in earlier papers is robust to the presence or absence of the reservation wage property and to whether the draws come from known or unknown distributions.

Keywords: job search, unknown distributions, reservation wage property, controlled experiments

JEL Classification: C91, D83, J64

1. Introduction

A prominent review of the state of the art of empirical labor economics begins as follows.

> *Understanding the labor market is central to understanding the modern economy. It is the "single" largest market in most economies . . . Complicating matters, workers in a labor market typically do not know . . . what firms have openings in what fields, and at what wages. They must devote time and energy to finding out. . . . the labor market is noisy; uncertainty and incomplete information are prevalent. It is also dynamic; acquiring and processing information take time* (Devine and Kiefer, 1991, p. 3).

What follows is a systematic exploration of about 600 studies of the economics of the labor market, with a central unifying theme:

The feature common to all studies in our review is a relevance to some aspect of search behavior in the labor market (Devine and Kiefer, 1991, p. 299).

Devine and Kiefer review many fine econometric studies of labor markets that use data from national economies. Such studies typically use job search models as maintained hypotheses for conducting econometric estimation. Much can be learned about labor markets from these studies, but they cannot examine the empirical validity of search theory itself because of limitations in the field data. Thus, search models imply that agent information on the distribution of wage offers, the length of search horizons, and the feasibility of recalling past wage offers are central determinants of an optimal search strategy. But none of these determinants are observable in the available field data. Therefore, controlled experiments have a unique role to play in studies of the empirical validity of search theory because an experimenter can control, and thereby observe within the experimental environment, the searchers' information about the distribution of wage offers, the length of their search horizons, and the feasibility of their recalling past wage offers.

There is a slowly growing literature on experimental tests of search theory. The present paper extends experimental tests of the theory to an environment in which the searcher does not know the distribution of wage offers. This is an especially challenging environment in which to test the theory because it introduces the possibility of designing an experiment in which search behavior must violate the intuitive reservation wage property in order to maintain consistency with the theory.

The *reservation wage property* is the feature that within any given time period of the search horizon there is one "reservation wage" or minimally acceptable wage offer: all offers equal to or greater than the reservation wage will be accepted and all offers less than the reservation wage will be rejected in that time period. Further, with an optimal *infinite* horizon search from a known distribution, the reservation wage path is level; that is, the reservation wage is constant over time (Mortensen, 1971). In contrast, with an optimal *finite* horizon search from a known distribution, the reservation wage is decreasing over time (Gronau, 1971).

Optimal job search from an unknown distribution *may* not exhibit the reservation wage property because of the potential "good news," "bad news" implications of Bayesian updating with the information provided by wage offers. Theoretically-optimal search from unknown wage offer distributions can have the property that some offers will be accepted that are *lower* than other offers that will be rejected in the same period of the search horizon. Thus the reservation wage property (or lowest acceptable wage path) may not exist. This seemingly puzzling outcome can occur when the searcher does not know in advance whether the search is from a relatively favorable ("high") or unfavorable ("low") wage offer distribution. Under those conditions, the same wage offer can contain both good news and bad news for the searching agent. An offer that is a priori relatively high ("good news") can imply that it is highly probable that search is from the favorable distribution, and such an offer can look unattractive when it is an *a posteriori* relatively low offer from the favorable distribution ("bad news"). We present experimental treatments for search from unknown distributions in which the reservation wage property does exist and treatments in which it does not exist. This is done in the context of investigating two central questions:

(a) Are earlier experimental findings, that wage offer search is consistent with the search duration and search income implications of theory, robust to search from unknown distributions?
(b) Does the empirical success or failure of search theory, in the context of unknown offer distributions, depend on whether or not the reservation wage property exists?

In our experiments, as in the naturally-occurring economy, the search horizon is finite and wage rates are discrete. The quantitative theoretical predictions that we test are derived from numerical solutions of a discrete wage, finite horizon search model that incorporates the salient characteristics of our experimental design. The numerical solutions are for risk neutral agents. Since the reservation wages of a risk averse agent are less than or equal to the reservation wages of a risk neutral agent, the solutions can be used to test both the risk neutral search model and the concave (risk averse or risk neutral) model. Two-sided tests based on the risk neutral model's solutions are used to test the risk neutral model. The concave model is tested with one-sided tests based on the solutions for the risk neutral model.

2. Experiments with search theory

Early experiments on job search were reported by Braunstein and Schotter (1981, 1982). Harrison and Morgan (1990) reported experiments on job search intensity. Hey (1982, 1987) and Kogut (1992) reported experiments on consumer price search. Grether et al. (1988) reported experiments on two-sided market price search.

We have been following an experimental research program involving systematic exploration of the theoretical predictions of finite horizon sequential search models. Cox and Oaxaca (1989) reported tests of theoretical predictions about the effects of varying the riskiness of the wage offer distribution, the probability of receiving an offer, the length of the search horizon, the rate of subsidy to search (or unemployment insurance), the cost of search, and the rate of interest. The tests reported in that paper were based on theoretical predictions of search duration and search income. The linear (or risk neutral) model survived those tests pretty well and the concave (risk neutral or risk averse) model survived them remarkably well. Direct tests of the reservation wage predictions of the linear and concave search models were reported in Cox and Oaxaca (1992a, 1992b). Tests of theoretical predictions about finite horizon search with certain and stochastic offer recall opportunities were reported in Cox and Oaxaca (1996). All of our previous search experiments involved search from known wage offer distributions.

3. A model of search from known and unknown wage offer distributions

We first introduce one specific version of the finite horizon model for search from a known distribution developed in Cox and Oaxaca (1989) and, subsequently, extend the model to include search from an unknown distribution.

A. Sequential search from a known wage offer distribution

Assume that the finite search horizon is T periods and that the probability that a job offer is received in any period in the search horizon is 1. The (integer value of the) wage offer is a realization of the random variable W with discrete density function,

$$g(w) = \begin{cases} Prob(W = w) & \text{for } w^{\ell} \leq w \leq w^{h} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Define the cumulative wage offer distribution function:

$$G(w) = \sum_{w^{\ell}}^{w} g(z) \tag{2}$$

The agent conducting a sequential search will have made t draws from the wage offer distribution if he is still searching at time t. In time period t, the probability that search yields a wage offer that is less than or equal to w is therefore $G(w)$.

Assume that if an offer is accepted in period t then wage payments begin in period $t + 1$ and continue through period $T + 1$. Let w_t be a possible reservation wage for period t. Define $I_t(w_t)$ as the time period-one discounted value of the expected utility of income from job search in period t. We consider the case in which a net subsidy to search in period t, denoted s_t, is paid in period t whether or not an offer is accepted. Thus, if the agent searches in period t, he receives the net subsidy, s_t, with certainty. With reservation wage w_t, the probability of not having an acceptable offer at time t is $1 - \sum_{w_t}^{w^h} g(z)$. If an acceptable offer is not available in period t, then the agent continues the search in period $t + 1$, with discounted expected utility $I_{t+1}(w_{t+1})$. Therefore, the expected utility from job search satisfies the equation of motion,

$$I_t(w_t) = (1+r)^{-(t-1)}u(s_t) + R_t \sum_{w_t}^{w^h} u(w)g(w) + \left(1 - \sum_{w_t}^{w^h} g(w)\right) I_{t+1}(w_{t+1}), \tag{3}$$

where $u(\cdot)$ is the agent's von Neumann-Morgenstern utility function normalized such that $u(0) = 0$, r is the rate of interest, and

$$\begin{aligned} R_t &= \sum_{\tau=t+1}^{T+1} (1+r)^{-(\tau-1)} \\ &= \sum_{\tau=t}^{T} (1+r)^{-\tau}. \end{aligned} \tag{4}$$

We define the *concave* model as the one in which $u(\cdot)$ is assumed to be strictly increasing and concave. The *linear* model is the special case where $u(\cdot)$ is linear. Thus, in the concave model the agent is assumed to be risk averse or risk neutral while, in the linear model, he is assumed to be risk neutral.

Optimal reservation wages can be derived by backward recursion in the following way. The returns to search are zero after the end of the search horizon; hence

$$I_{T+1}(w_{T+1}) = 0, \quad \text{for all } w_{T+1}. \tag{5}$$

Equations (3) and (5) imply

$$I_T(w_T) = (1+r)^{-(T-1)}u(s_T) + R_T \sum_{w_T}^{w^h} u(w)g(w). \tag{6}$$

$I_T(\cdot)$ is decreasing in w_T; therefore the optimal reservation wage in period T equals zero:

$$w_T^* = 0 \tag{7}$$

Optimal reservation wages for other periods are derived as follows. Collecting terms in Eq. (3) and setting $w_{t+1} = w_{t+1}^*$ yields

$$I_t(w_t) = I_{t+1}(w_{t+1}^*) + (1+r)^{-(t-1)}u(s_t) + \sum_{w_t}^{w^h}[R_t u(w) - I_{t+1}(w_{t+1}^*)]g(w). \tag{8}$$

The optimal reservation wage for period t, w_t^*, is the discrete value of w_t that maximizes $I_t(w_t)$. The bracketed term in Eq. (8) will be positive, zero, or negative as $w \gtreqless u^{-1}(I_{t+1}(w_{t+1}^*)/R_t)$. Therefore, the optimal reservation wage, w_t^*, $t = 1, 2, \ldots, T-1$, is the discrete value that is not less than, and closest to, the greater of 0 and $u^{-1}(I_{t+1}(w_{t+1}^*)/R_t)$.

B. *Sequential search from an unknown wage offer distribution*

We incorporate search from an unknown distribution into the sequential search model in a way that yields sharp testable implications. Let offers be generated from one of two discrete uniform distributions:

$$g_i(w) = \begin{cases} \dfrac{1}{k_i} & \text{for } w^{\ell i} \le w \le w^{h_i} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

for $k_i = w^{h_i} - w^{\ell_i} + 1 > 0$, $i = 1, 2$. Let $w^{\ell_1} < w^{\ell_2}$ and $w^{h_1} < w^{h_2}$. Then distribution 1, with support $\{w^{\ell_1}, w^{\ell_1}+1, \ldots, w^{h_1}-1, w^{h_1}\}$, is clearly the unfavorable or relatively low wage offer distribution and distribution 2, with support $\{w^{\ell_2}, w^{\ell_2}+1, \ldots, w^{h_2}-1, w^{h_2}\}$, is the favorable or relatively high wage offer distribution. Consider pairs of distributions whose supports have a non-null intersection such that $w^{\ell_2} < w^{h_1}$. Bayesian updating is all or none since offers contained in the intersection of the distributions' supports provide no information for updating and offers outside the intersection reveal which distribution generated the offer.

Which distribution will actually be generating the offers is unknown *ex ante*, but assume that the searcher knows that each distribution has a probability of 0.5 of being the actual offer distribution. The a priori density function for wage offers is

$$g(w) = \begin{cases} \dfrac{0.5}{k_1} & \text{for } w^{\ell_1} \leq w \leq w^{\ell_2} \\ \dfrac{0.5}{k_1} + \dfrac{0.5}{k_2} & \text{for } w^{\ell_2} \leq w \leq w^{h_1} \\ \dfrac{0.5}{k_2} & \text{for } w^{h_1} < w \leq w^{h_2} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

Let $k_1 = k_2 = k$; then $g(w)$ can be rewritten as

$$g(w) = \begin{cases} \dfrac{0.5}{k} & \text{for } w^{\ell_1} \leq w \leq w^{\ell_2} \\ \dfrac{1}{k} & \text{for } w^{\ell_2} \leq w \leq w^{h_1} \\ \dfrac{0.5}{k} & \text{for } w^{h_1} < w \leq w^{h_2} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

In other words, the *ex ante* density function, $g(w)$, for drawing from either distribution 1 or distribution 2 with probability 0.5 ("drawing from an unknown distribution") is the same as the density function for drawing from a single distribution that is the 0.5 mixture of distributions 1 and 2. The *a posteriori* density function is $g(w)$ so long as all of the realizations of the wage offers have been from the intersection of the supports of distributions 1 and 2. The first draw outside this intersection causes a Bayesian to update the *a posteriori* density function to be either $g_1(w)$ or $g_2(w)$, depending on whether the offer is less than w^{ℓ_2} or greater than w^{h_1}.

Let the cumulative wage offer distribution function for the ith distribution be given by

$$G_i(w) = \sum_{w^{\ell_i}}^{w} g_i(z), \quad i = 1, 2.$$

An offer less than w^{ℓ_2} or greater than w^{h_1} would reveal respectively, that distribution 1 or distribution 2 was the actual offer distribution. Therefore, the probability that an offer in any given period would be revealing is

$$\pi = (0.5)\{G_1(w^{\ell_2} - 1) + [1 - G_2(w^{h_1})]\}.$$

In optimal search from an unknown distribution, the reservation wage property is replaced by an optimal decision rule about which sets of offers will be accepted and which will be rejected. This optimal decision rule in some cases will be the reservation wage property, and in other cases the reservation property will not exist. As long as a searcher is searching and has not received an informative offer, he will assign probabilities to outcomes associated with the distribution $g(w)$. If the searcher is still searching and receives a revealing or informative offer, he will adopt the reservation wage path appropriate to the revealed distribution. The optimal decision rule is derived as follows. It is assumed that no revealing offers have been received prior to each period t in the search horizon. For the set of offers that are not informative, partition the set into conditional acceptable and unacceptable offers based on the reservation wage path for the mixed distribution $g(w)$. For the set of offers that would reveal that the distribution is $g_1(w)$, partition the set into conditional acceptable and unacceptable offers based on the reservation wage for $g_1(w)$. Similarly, the set of offers that would reveal that the distribution is $g_2(w)$ is partitioned into conditional acceptable and unacceptable offers based on the optimal reservation wage for $g_2(w)$. The final acceptance and rejection sets are the union of the separately-calculated conditional acceptance and rejection sets.

4. Experimental design

The experiments use a paired design of drawing offers from "known" and "unknown" distributions. The four known distributions, KN1–KN4, are presented in Table 1. The random number generator is a bingo cage. For the distribution KN1, the bingo cage contains one each of balls numbered 1–2 and 11–12 and two each of balls numbered 3–10; thus the probability of drawing 1, 2, 11, or 12 is 0.05 and the probability of drawing any integer from 3 through 10 is 0.10. The other known distributions are similar and are presented in Table 1.

The four unknown distributions, UNK1–UNK4, are also presented in Table 1. The random number generators are a coin and two bingo cages. For the distribution UNK1, a coin is first flipped to determine which of two bingo cages will be used; then the indicated cage is used for the subsequent draws. For UNK1, cage I contains one each of balls numbered 1–10 and cage II contains one each of balls numbered 3–12. The other unknown distributions are similar and are presented in Table 1.

Before the coin is flipped, the probability of drawing 1, 2, 11, or 12 from UNK1 is 0.05 and the probability of drawing any integer from 3–10 is 0.10; these are the same probabilities as in KN1. An analogous a priori equivalence exists between KNi and UNKi, for $i = 2, 3, 4$.

The outcome of the coin flip is observed by the experimenter but is *not* observed by the subject. The subject does observe the draws from a bingo cage. Bayesian updating for draws from UNK1 is "all or none." For example, if 1 or 2 is drawn from UNK1 then a Bayesian agent will assign probability 1 to the event that the draws came from cage I; similarly, if an 11 or 12 is drawn from UNK1 then the Bayesian updated probability is 1 that the draws came from cage II. Drawing any number from 3 through 10 from UNK1 provides no information for updating by a Bayesian agent; in that event such an agent will assign the same probabilities to outcomes as he would for draws from KN1. An analogous "all or none" Bayesian updating exists for UNKi, for $i = 2, 3, 4$.

Comparisons among the unknown distributions reveal the following. Cage I contains balls numbered 1–10 for each of the UNKi, $i = 1, 2, 3, 4$, distributions. The differences among these distributions come from the differing contents of cage II. Note that, after the coin is flipped, the probability is 0.2 that any single draw from UNK1 will reveal which

Table 1. Probability distributions.

Known Distributions

KN1 The bingo cage contains:

(i) One each of balls numbered 1–2 and 11–12;

(ii) Two each of balls numbered 3–10

KN2 The bingo cage contains:

(i) One each of balls numbered 1–4 and 11–14;

(ii) Two each of balls numbered 5–10

KN3 The bingo cage contains:

(i) One each of balls numbered 1–6 and 11–16;

(ii) Two each of balls numbered 7–10

KN4 The bingo cage contains:

(i) One each of balls numbered 1–8 and 11–18;

(ii) Two each of balls numbered 9–10

Unknown Distributions

UNK1 The random number generators:

(i) A coin;

(ii) Bingo cage I contains one each of balls numbered 1–10;

(iii) Bingo cage II contains one each of balls numbered 3–12

UNK2 The random number generators:

(i) A coin;

(ii) Bingo cage I contains one each of balls numbered 1–10;

(iii) Bingo cage II contains one each of balls numbered 5–14

UNK3 The random number generators:

(i) A coin;

(ii) Bingo cage I contains one each of balls numbered 1–10;

(iii) Bingo cage II contains one each of balls numbered 7–16

UNK4 The random number generators:

(i) A coin;

(ii) Bingo cage I contains one each of balls numbered 1–10;

(iii) Bingo cage II contains one each of balls numbered 9–18

bingo cage is being used. The analogous probabilities for UNK2, UNK3, and UNK4 are 0.4, 0.6, and 0.8.

The unknown distributions were chosen so that the reservation wage property theoretically exists for UNK1 and UNK2 but does not exist for UNK3 and UNK4. This can be explained as follows. So long as all of the balls that have been drawn from UNKi could have come from either cage I or cage II, a Bayesian agent will believe that the distribution of wage offers is the same as KNi; hence the agent's reservation wages will be the same as they would be if he were drawing from KNi. However, as soon as the Bayesian agent draws a ball from UNKi that could *only* have come from cage I or from cage II, the agent's reservation

Table 2. Acceptance and rejection wages for UNK1.

Period	Acceptance set	Rejection set
1	9–12	1–8
2	·	·
3	·	·
4	·	·
5	·	·
6	9–12	1–8
7	8–12	1–7
8	·	·
9	·	·
10	·	·
11	·	·
12	8–12	1–7
13	7–12	1–6
14	·	·
15	7–12	1–6
16	6–12	1–5
17	6–12	1–5
18	5–12	1–4
19	4–12	1–3
20	1–12	—

wages will be those for the discrete uniform distribution of offers for that cage. Because the reservation wage path for the 0.5 mixture of the cage I and cage II distributions (i.e., the a priori UNKi distribution) is distinct from the reservation wage paths for the cage I and cage II distributions, a Bayesian agent might be willing to accept an offer w_1 that reveals that the draws are coming from the unfavorable cage I whereas he would reject an offer w_2, such that $w_2 > w_1$, that could have come from either cage I or cage II or could have come only from cage II. Thus the reservation wage property may not exist.

Tables 2–5 present the acceptance and rejection wages for a risk neutral Bayesian agent drawing offers from UNK1–UNK4. The acceptance sets in Tables 2 and 3 contain only consecutive integers; therefore, the reservation wage property exists for drawings from the UNK1 and UNK2 distributions. In contrast, the acceptance sets for some periods in Tables 4 and 5 contain some non-consecutive integers. For example, Table 5 informs us that a risk neutral Bayesian optimal searcher, drawing from the distribution UNK4, would accept an offer of 8 in periods 1–5 but would reject (higher) offers of 9–14 for those same periods. Why? Because drawing an 8 informs the agent that the draws are coming from cage I and 8 is not less than the period 1–5 optimal reservation wages for the cage I discrete uniform distribution of offers. In contrast, drawing a 9 or 10 would not inform the agent which cage

Table 3. Acceptance and rejection wages for UNK2.

Period	Acceptance set	Rejection set
1	10–14	1–9
2	·	·
3	·	·
4	·	·
5	·	·
6	·	·
7	10–14	1–9
8	9–14	1–8
9	·	·
10	·	·
11	·	·
12	9–14	1–8
13	8–14	1–7
14	·	·
15	8–14	1–7
16	7–14	1–6
17	7–14	1–6
18	6–14	1–5
19	4–14	1–3
20	1–14	—

was being used, and such offers do not exceed the risk neutral optimal reservation wages for periods 1–5 for drawings from the 0.5 mixture of the cage I and cage II distributions. Furthermore, drawing any number from 11 through 14 would inform the searcher that cage II was being used, and such offers do not exceed the period 1–5 reservation wages for drawings from cage II. Thus the reservation wage property does not exist for drawings from UNK4. For similar reasons, the property also does not exist for drawings from UNK3.

Figures 1–4 graphically depict the reservation wage paths corresponding to the mixture, cage I, and cage II distributions associated with the UNK1–UNK4 treatments. To illustrate the logic underlying the existence or nonexistence of the reservation wage property we will consider the UNK1 and UNK3 treatments. For the UNK1 treatment, offers between 3 and 10 (inclusive) are noninformative (see Table 1). Faced with a noninformative offer, a risk neutral Bayesian would assume the mixture distribution corresponding to KN1. As discussed above, an offer of 1 or 2 reveals cage I as the wage offer distribution and an offer of 11 or 12 reveals cage II as the wage offer distribution. Figure 1 shows that in period 1 the minimum acceptable wage given a noninformative offer is 9. Hence, conditional on receiving a noninformative offer, only offers of 9 or 10 would be accepted. An offer of 1 or 2 in period 1 would be rejected because 8 is the minimum acceptable offer for the cage I distribution

Table 4. Acceptance and rejection wages for UNK3.[a]

Period	Acceptance set	Rejection set
1	13–16	1–12
2	·	·
3	·	·
4	·	·
5	·	·
6	·	·
7	13–16	1–12
8	12–16	1–11
9	12–16	1–11
10	10, 12–16	1–9, 11
11	·	·
12	10, 12–16	1–9, 11
13	9–16	1–8
14	6, 9–16	1–5, 7–8
15	6, 9–16	1–5, 7–8
16	6, 8–16	1–5, 7
17	5–16	1–4
18	4–16	1–3
19	3–16	1–2
20	1–16	—

[a]The acceptance and rejection sets for each period are derived by assuming that all draws in previous periods in the trial were uninformative about which cage was being used.

in period 1. An offer of 11 or 12 would be accepted in period 1 because the minimum acceptable offer for the cage II distribution is 10 in this period. Hence the acceptance set is {9, . . . , 12} and the rejection set is {1, . . . , 8}. This outcome corresponds to the reservation wage property with 9 as the minimum acceptable wage offer. Similar reasoning applies to the remaining periods and to the UNK2 treatment. Thus, the reservation wage property holds for the UNK1 and UNK2 treatments.

Now consider the UNK3 treatment. According to Table 1, an offer between 7 and 10 (inclusive) is noninformative so that the searcher would assume the mixture distribution corresponding to KN3. On the other hand, offers between 1 and 6 or between 11 and 16 reveal the wage offer distribution to be cage I or cage II, respectively. Figure 3 shows that in period 1 the minimum acceptable wage given a noninformative offer is 12. Consequently, no offer would be accepted in this period that is noninformative. An offer between 1 and 6 (inclusive) would be rejected because 8 is the minimum acceptable offer for the cage I distribution in period 1. An offer between 11 and 16 would reveal cage II as the wage offer

Table 5. Acceptance and rejection wages for UNK4.[a]

Period	Acceptance set	Rejection set
1	8, 15–18	1–7, 9–14
2	·	·
3	·	·
4	·	·
5	8, 15–18	1–7, 9–14
6	8, 14–18	1–7, 9–13
7	7–8, 14–18	1–6, 9–13
8	·	·
9	·	·
10	7–8, 14–18	1–6, 9–13
11	7–8, 13–18	1–6, 9–12
12	·	·
13	7–8, 13–18	1–6, 9–12
14	6–8, 10, 12–18	1–5, 9, 11
15	6–8, 10, 12–18	1–5, 9, 11
16	6–18	1–5
17	5–18	1–4
18	4–18	1–3
19	3–18	1–2
20	1–18	—

[a]The acceptance and rejection sets for each period are derived by assuming that all draws in previous periods in the trial were uninformative about which cage was being used.

distribution and accordingly the minimum acceptable offer would be 13. Therefore, the acceptance set in period 1 is $\{13, \ldots, 16\}$ and the rejection set is $\{1, \ldots, 12\}$. This outcome corresponds to the reservation wage property with 13 as the minimum acceptable wage offer. In fact, this reasoning establishes that the optimal decision rule is consistent with the reservation wage property until period 10. In period 10, the reservation wage corresponding to a noninformative offer is 10. This means that 10 is the only noninformative offer that would be accepted. Any offer between 1 and 6 would be rejected because the minimum acceptable offer from cage I is 7 in period 10. Of the cage II revealing offers (11 through 16), only 12 through 16 are acceptable because the cage II reservation wage is 12 in this period. Hence, the acceptable offer set in period 10 is $\{10, 12, \ldots, 16\}$ and the rejection set is $\{1, \ldots, 9, 11\}$. It is clear that the reservation wage property does not hold for this period because an offer of 11 would be rejected but an offer of 10 would be accepted. Therefore, the reservation wage property does not hold for the UNK3 treatment. Similar reasoning shows that the reservation wage property does not exist for the UNK4 treatment either. In

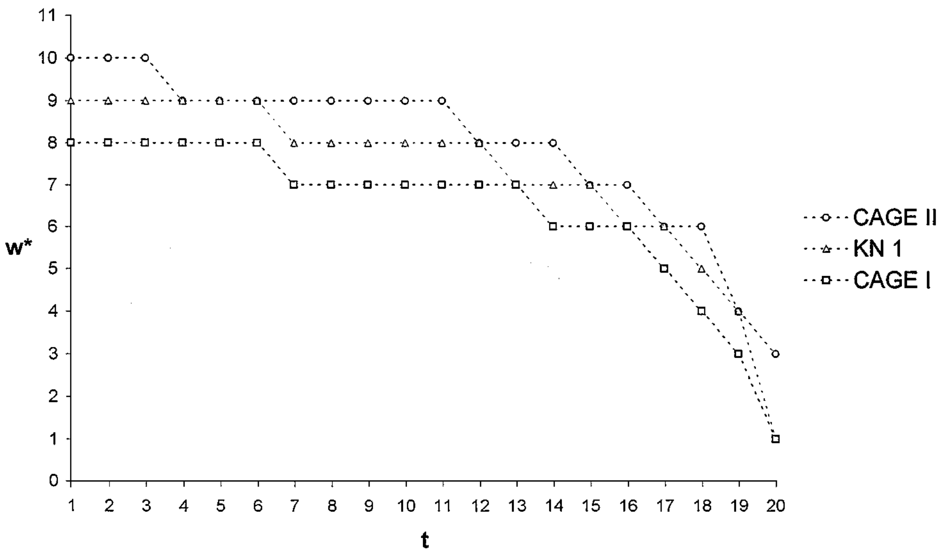

Figure 1. Reservation wage paths for UNK1 treatment.

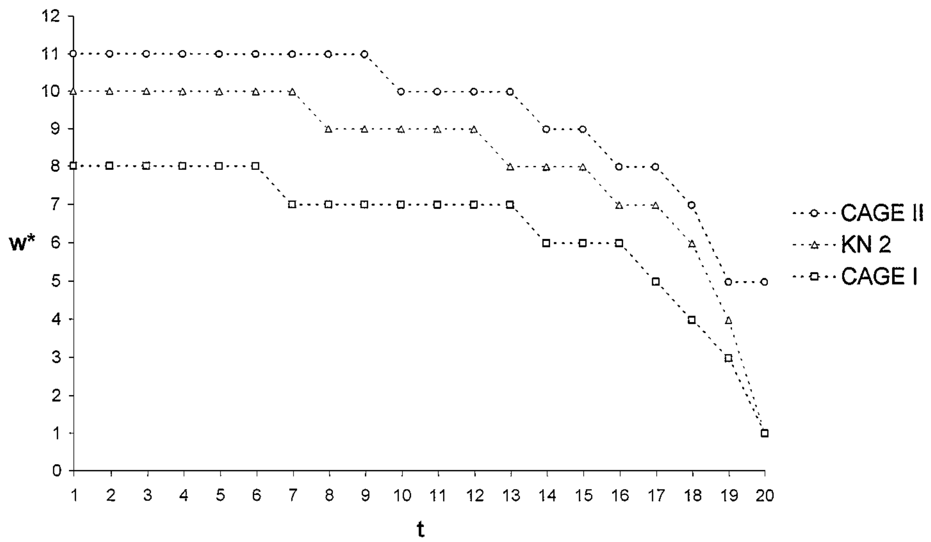

Figure 2. Reservation wage paths for UNK2 treatment.

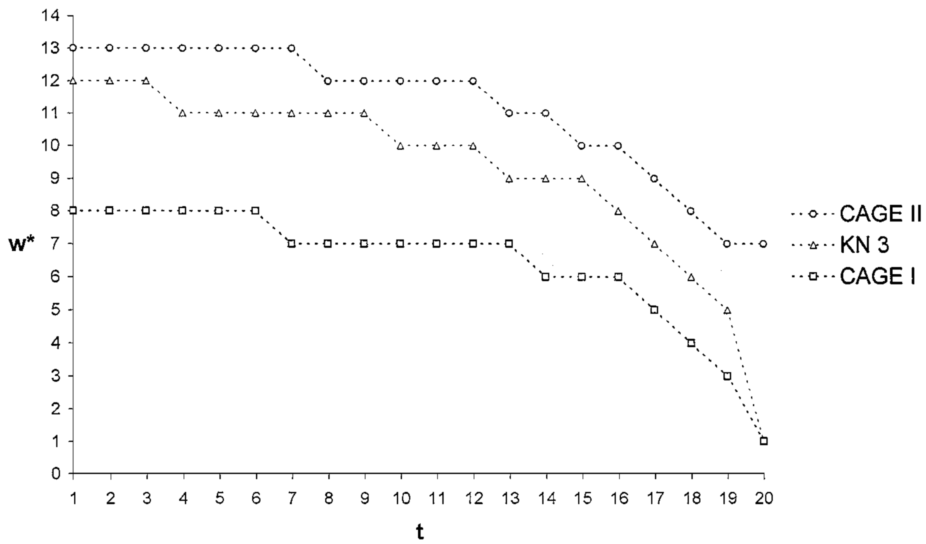

Figure 3. Reservation wage paths for UNK3 treatment.

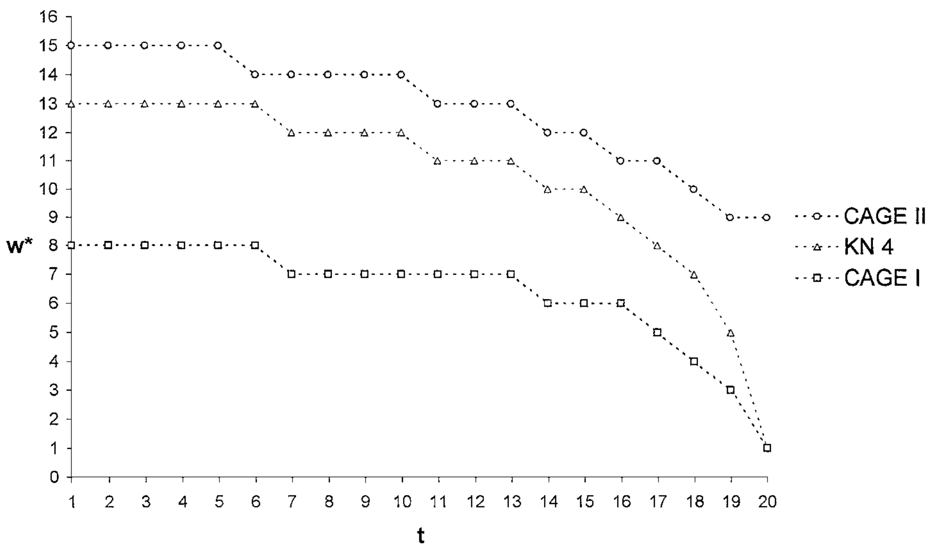

Figure 4. Reservation wage paths for UNK4 treatment.

fact, for the UNK4 treatment the optimal decision rule is not consistent with the reservation wage property in any period from 1 through 15.

A. *Experiment A*: We shall report the data from two experiments. Thirty distinct subjects participated in experiment A. This experiment included ten trials, each with a maximum of 20 periods (the finite horizon). The ten trials included the drawing of offers from five probability distributions in the following sequence: UNK4, UNK4, UNK2, UNK2, KN4, KN4, KN2, KN2, UNK4, UNK4. Subject responses in the first two (UNK4) trials can be compared with their responses in the last two (UNK4) trials to see if they "return to baseline," i.e., to ascertain whether learning or other sequencing effects might be confounded with treatment effects in the data. Subject responses in (all of) the UNK4 trials can be compared with their responses in the KN4 trials to see whether the responses in the KN4 trials are the same as the responses in those periods in the UNK4 trials for which a Bayesian agent would be using the a priori UNK4 probabilities. Analogous comparisons can be made using data from the UNK2 and KN2 trials. Data from the UNK2 and UNK4 trials can be used to test for effects on subjects' decisions of existence of the reservation wage property. Data from all of the trials can be used to test the risk neutral search model and the concave (risk neutral or risk averse) search model.
B. *Experiment B*: The other experiment, called experiment B, included 30 distinct subjects who did not participate in experiment A. This experiment also included ten trials, each with a maximum of 20 periods. The ten trials in experiment B included the drawing of offers from five probability distributions in the following sequence: KN1, KN1, KN3, KN3, UNK1, UNK1, UNK3, UNK3, KN1, KN1. All of the same types of tests can be done with the experiment B data as with the experiment A data.
C. *Payoffs and subjects*: The risk neutral search model can be used to calculate the expected monetary payoff to an optimal risk neutral searcher from participating in one of these experiments. The expected payoff to such an agent for experiment A is $24.68. The analogous expected payoff for experiment B is $20.36. The actual average subject payoffs were $21.12 in experiment A and $19.15 in experiment B. The experiments lasted about 45 minutes, on average. The subjects were undergraduate students at the University of Arizona.

5. Experimental procedures

The experiments involved the drawing of wage offers from four known distributions and four unknown distributions. Drawing from a "known" discrete uniform distribution was operationalized by showing each subject the numbers on 20 balls that were put into a bingo cage in the subject's presence. Drawing from an "unknown" discrete uniform distribution was operationalized as follows. A subject was first shown the numbers on 10 balls that were put into a bingo cage in the subject's presence. The subject was next shown the numbers on another 10 balls that were put into a second bingo cage in the subject's presence. The two bingo cages were of the same semi-transparent plastic type which were spray-painted with grey paint in order to make them opaque. After placing the two sets of balls in the cages, the experimenter put the cages one at a time behind an opaque screen. The experimenter next removed the cages one at a time, in random order, from behind the screen and placed them on a surface about six feet from where a subject was seated. This procedure was followed in order to obscure any possible subtle differences between the two cages even though they appeared identical to the experimenters. (The subject previously had been asked to look behind the screen in order to ascertain that there were no other bingo cages in the room other than the two with known contents.) After both cages were removed from behind the screen, the subject was asked to decide which cage (the one "on the right" or the one "on the left") would be selected if a flipped coin turned up "heads." Then a coin was flipped, the outcome (heads or tails) was observed by the subject and the experimenter, and the randomly-selected bingo cage was adopted for the draws of "wage offers." Of course, the subject was not informed of the contents of the cage that had been selected.

After selecting a cage by coin flip, the experimenter proceeded to draw one ball from the cage, with replacement, each period until the subject decided to accept an offer and terminate that trial in the experiment. Each ball drawn was shown to the subject, and the subject's attention was called to the experimenter's action of returning each drawn ball to the cage before drawing another ball.

Subject instructions for each experiment were divided into three parts. For example, in experiment A, part I of the instructions was for the first two UNK4 trials and for the UNK2 trials. Part II of the instructions was for the KN4 and KN2 trials. Finally, part III of the instructions was for the last two UNK4 trials. The three parts of the instructions were given to the subjects at different times; each part was administered immediately before the subject began the specific trials explained in that part. Each part of the instructions explained the procedures, decisions, and data recording forms for the relevant part of the experiment. Parts I and II of the instructions led the subjects through sample trials in order to help them acquire familiarity with the structure of the experiments and the data recording forms.

The recording forms for KN*i* trials listed the balls in the bingo cage at the top of the form. Five columns on the forms were used as follows. Column A listed the period numbers (1–20). Column B was a column in which the subjects recorded the numbers on the balls drawn from the bingo cage. Column C listed the "money conversion factors" for each of the 20 periods; these were annuity factors to be applied to the numbers drawn from the bingo cage (R_t in Eq. (4), above). Since the rate of interest was zero in the two experiments reported in this paper, the annuity factor for any period t was $21 - t$, for $t = 1, 2, \ldots, 20$. Column D was a column in which the subjects recorded the figures for "earnings from stopping"; these figures were calculated by multiplying the money conversion factors times the numbers drawn. Column E was a column in which the subjects recorded, each period, their decisions to "stop" or to "continue" the search. After a trial was completed, the subject's earnings were recorded at the bottom of the record sheet.

The recording forms for the UNK*i* trials were similar to those for the KN*i* trials discussed above. The contents of the two bingo cages involved in an UNK*i* trial were listed at the top of the form. In addition to all of the columns on a KN*i* recording form, an UNK*i* form also had columns for recording the lowest and highest numbers drawn up through any period in a trial.

The subject instructions and data recording forms for experiment A are contained in an appendix that is available on request. The instructions and forms for experiment B are similar.

6. Empirical results

For the purposes of this paper, we adopt the 10% level of significance as the cutoff for statistical significance. The results of formal statistical tests are reported as *p* values so that the reader may judge the strength of a rejection or failure to reject for each statistical test.

A. Search terminations consistent with the linear and concave search models

Figures 5 and 6 present the distributions of model violations by individual subjects in the two experiments. 12 out of the 30 subjects in each experiment never violated the concave model. In comparison, only 2 subjects in experiment A and 3 in experiment B never violated the risk neutral model. 20 of the 30 subjects in experiment A and 22 of the 30 subjects in experiment B did not violate the concave model more than once. In comparison, 22 subjects in experiment A and 20 in experiment B had no more than 3 violations of the risk neutral model.

Table 6 reports the numbers and proportions of searches that (a) correspond to the general concave (risk averse or risk neutral) model, i.e. that terminate at or before the periods predicted by the linear (risk neutral) model conditional on the draws and (b) correspond to the linear model, i.e. terminate at exactly the periods predicted by the linear model conditional on the draws. The first and second running of a baseline treatment are denoted

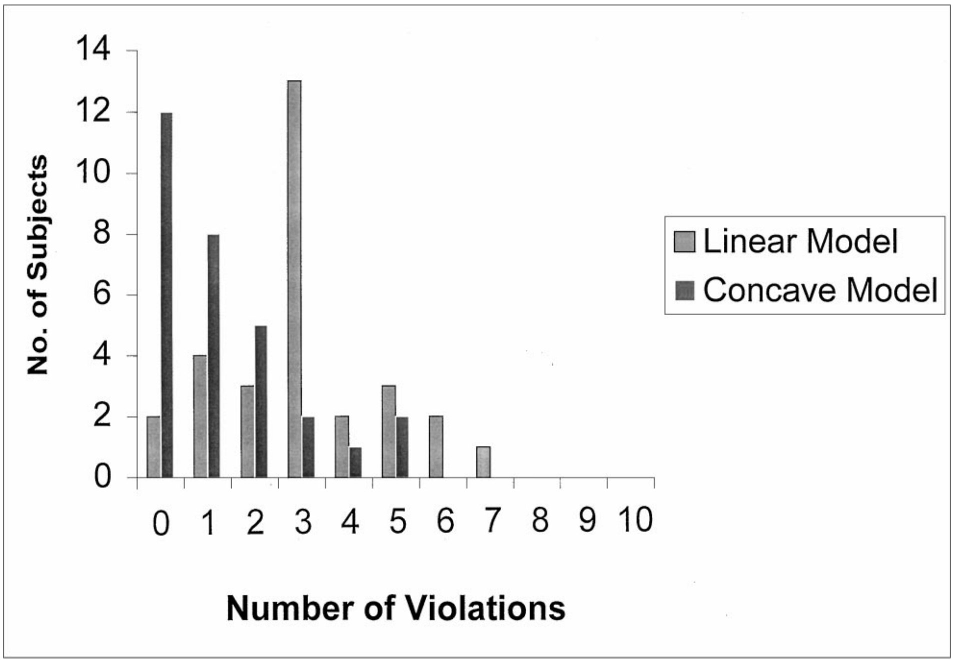

Figure 5. Distribution of model violations in experiment A.

Table 6. Consistent search terminations.

Treatment	Concave model Ratio	Concave model (%)	Linear model Ratio	Linear model (%)
Experiment A				
UNK4(i)	50/60	83.3	38/60	63.3
UNK2	51/60	85.0	35/60	58.3
KN4	54/60	90.0	44/60	73.3
KN2	51/60	85.0	47/60	78.3
UNK4(ii)	56/60	93.3	45/60	75.0
Total A	262/300	87.3	209/300	69.7
Experiment B				
KN1(i)	50/60	83.3	39/60	65.0
KN3	57/60	95.0	39/60	65.0
UNK1	48/60	80.0	43/60	71.7
UNK3	57/60	95.0	44/60	73.3
KN1(ii)	57/60	95.0	48/60	80.0
Total B	269/300	89.7	213/300	71.0
Total A and B	531/600	88.5	422/600	70.3

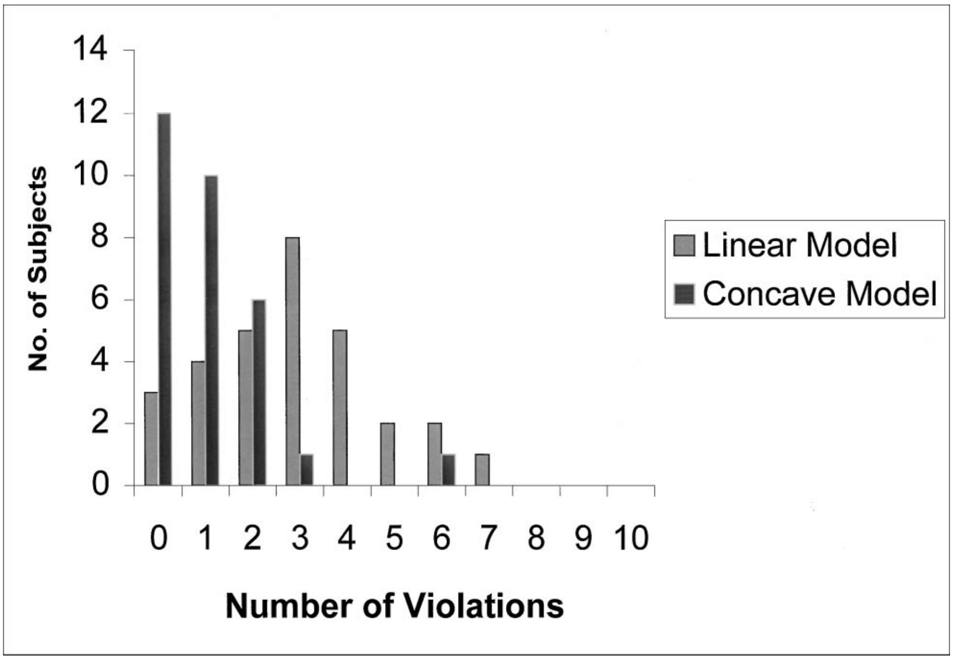

Figure 6. Distribution of model violations in experiment B.

by (i) and (ii). As in our previous search experiments, Cox and Oaxaca (1989, 1992a, 1992b, 1996), the results are strongly consistent with the general concave model. Approximately 89% of the searches terminated at or before the periods predicted by the linear model. On the other hand, the success rate for the linear model is somewhat lower in this round of experiments compared to earlier search experiments (70% versus 75%).

In interpreting our findings in terms of the linear and concave models, it might be useful to make comparisons with the predictions of naive models. Such comparisons help one to calibrate the significance of empirical consistency with the predictions of the formal search model presented in this paper. In Cox and Oaxaca (1992b), a naive model was tested in which the decision rule was to accept any offer in excess of the median from the conditional wage offer distribution and reject all others (except in the last period of the search horizon). In keeping with the spirit of naivete, this decision rule is invariant with respect to the treatment. Based on direct tests using revealed precommitment (reservation) wages, we were able to reject both the risk neutral (linear) model and the naive model. The risk averse or risk neutral (concave) model was not rejected.

In Cox and Oaxaca (1996), experiments with search recall yielded evidence against the concave model in the form of behavior appearing to be more risk averse in the presence of recall opportunities. Of course the problem is that recall opportunities reduce the riskiness of job search. This is a question of internal consistency. While all of the empirical evidence to date consistently reveals one-sided deviations from risk neutrality in the direction predicted by the concave model, it might be useful to compare these results against the predictions of another naive model. A naive decision rule that is suitable for comparison with the concave model is one in which in each period of search an offer is accepted with probability p and rejected with probability $1 - p$. The probability p should be invariant with respect to the treatments or else the model is not naive. For a given search horizon, the expected duration of search would be invariant with a change in treatments. Our previous findings in Cox and Oaxaca (1989) shed light on this question. The observed mean durations of search for nine treatments are reproduced in Table 7. We see that there is considerable variation in mean observed search durations, ranging from a low of 2.85 periods to a high of 6.267

Table 7. Mean search durations (Cox and Oaxaca, 1989).

Treatment	$\bar{D}$
Baseline 1A	4.783
Baseline 1B	3.967
Baseline 2A	3.933
Baseline 2B	3.483
Interest rate	4.767
Subsidy	6.267
Risk	3.350
Cost	2.850
Probability	5.867

periods. These results strongly reject the proposition that a simple probability decision rule can explain the data as well or better than the concave model.

B. Relative search termination consistency for known and unknown distributions

Some evidence on behavioral differences when treatments with known distributions are compared with those with unknown distributions is provided in Table 6. Chi-square contingency table tests were used to informally gauge whether or not apparent differences in success rates were significant. The success rates for UNK4(i) and KN4 relative to both the general concave model and the linear model are not significantly different. These same results obtain for a comparison of the success rates for UNK4(ii) and KN4. In the case of UNK2 and KN2, the success rates are identical with respect to the concave model but are significantly different with respect to the linear model. Thus for experiment A, we can say that the introduction of uncertainty over the wage offer distribution does not have any appreciable effect on the success rates for the concave model. In experiment B the success rates for KN1(i) and UNK1 relative to both the concave model and the linear model are not significantly different. However, the success rates for KN1(ii) and UNK1 are significantly different with respect to the concave model but not with respect to the linear model. For KN3 and UNK3 the success rates relative to the concave model are identical, and the difference in the linear model's success rates are not statistically significant. Thus we can say that the introduction of uncertainty over the wage offer distribution in experiment B does not have any appreciable effect on the linear model's success rates.

C. Search termination consistency in the presence and absence of the reservation wage property

What about the success rates between treatments with the reservation wage property and those without the reservation wage property? The success rates for UNK4(i) and UNK2 are virtually identical for the general concave model, but are significantly different for the linear model. The results for UNK4(ii) and UNK2 lead to the same inferences. Thus for experiment A, the existence or nonexistence of the reservation wage property does not appreciably affect the success rates for the concave model. In experiment B the success rates for UNK1 and UNK3 are significantly different for the concave model but not for the linear model. Thus the existence or nonexistence of the reservation wage property does not appreciably affect the success rates for the linear model in experiment B. The contrast between experiments A and B with respect to the effects of the reservation wage property on success rates is the same as the contrast with respect to certainty about the wage offer distribution. In other words, treatment effects have no significant impacts on the success rates for the concave model in experiment A and the linear model in experiment B.

Comparing across the two experiments in Table 6, one cannot reject the hypothesis that the overall success rates are the same for experiment A and experiment B. We interpret this finding to mean that there is no difference in the decision-making behavior of the subjects across experiments. We also note that the success rates tend to be lower in the earlier treatments for both experiments. This is especially apparent when looking at the linear model's success rates. Since experiments A and B reverse the order of appearance of treatments with unknown versus known distributions, any learning effects that may be present are not likely to be driven by uncertainty over the distribution from which offers are drawn. One cannot reject the hypothesis of return to baseline for experiment A in terms of differences in success rates for both the general concave model and the linear model. However, for experiment B the chi-square contingency table tests indicate that one can reject a return to baseline in terms of differences in success rates for both the general concave model and the linear model. We investigate further the issue of learning effects by conducting formal parametric and nonparametric tests for a return to baseline. The results of those tests are discussed below.

Our first set of formal statistical tests pertain to the deviations of observed search durations from the predicted search durations of the linear model, conditional on the actual draws from the wage offer distributions. Let $\bar{D}_i$ represent the mean duration of search for treatment i, and let $\bar{D}^{in}$ represent the mean of the predicted durations of search for treatment i conditional on the actual draws.[1] In the case of the general concave model, the hypothesis test is specified as

$$H_0 : E(\bar{D}^i - \bar{D}^{in}) \leq 0, \quad H_1 : \sim H_0.$$

For the linear model, the hypothesis test is specified as

$$H_0 : E(\bar{D}^i - \bar{D}^{in}) = 0, \quad H_1 : \sim H_0.$$

Table 8 presents the p values corresponding to the parametric matched pairs test and the nonparametric Fisher sign test. First consider the general concave model. In experiment A

Table 8. Mean/median search duration tests of the concave and linear models—p values.

	$H_0 : E(\bar{D}^i - \bar{D}^{in}) \leq 0$		$H_0 : E(\bar{D}^i - \bar{D}^{in}) = 0$	
Treatment	Matched pairs test ($N = 60$)	Fisher sign test	Matched pairs test ($N = 60$)	Fisher sign test
Experiment A				
UNK4(i)	0.204	0.738 ($N = 22$)	0.407	0.832 ($N = 22$)
UNK2	0.070	0.946 ($N = 25$)	0.767	0.230 ($N = 25$)
KN4	0.362	0.895 ($N = 16$)	0.724	0.454 ($N = 16$)
KN2	0.019	0.133 ($N = 13$)	0.037	0.266 ($N = 13$)
UNK4(ii)	0.692	0.982 ($N = 15$)	0.617	0.118 ($N = 15$)
Experiment B				
KN1(i)	0.093	0.668 ($N = 21$)	0.187	0.999 ($N = 21$)
KN3	0.990	0.999 ($N = 21$)	0.021	0.002 ($N = 21$)
UNK1	0.014	0.072 ($N = 17$)	0.028	0.144 ($N = 17$)
UNK3	0.955	0.998 ($N = 16$)	0.091	0.022 ($N = 16$)
KN1(ii)	0.930	0.981 ($N = 12$)	0.139	0.146 ($N = 12$)

Table 9. Kolmogorov-Smirnov Goodness-of-fit test—p values.

Treatment	Concave model	Linear model
Experiment A		
UNK4(i)	$p > 0.10$	$p > 0.10$
UNK2	$p > 0.10$	$p > 0.10$
KN4	$p > 0.10$	$p > 0.10$
KN2	$p > 0.10$	$p > 0.10$
UNK4(ii)	$p > 0.10$	$p > 0.10$
Experiment B		
KN1(i)	$p > 0.10$	$p > 0.10$
KN3	$p = 0.99$	$p > 0.10$
UNK1	$0.05 < p < 0.10$	$0.10 < p < 0.20$
UNK3	$p > 0.10$	$p > 0.10$
KN1(ii)	$p = 0.99$	$p > 0.10$

the concave model survives quite well. Only in the case of the matched pairs test for treatment UNK2 and KN2 is the concave model rejected at conventional levels of significance. The linear model also survives remarkably well. The only exception is again treatment KN2 in which the linear model can be rejected on the basis of the matched pairs test.

In experiment B the concave model generally survives although not quite as well as in experiment A. The concave model is rejected for treatment KN1(i), but not KN1(ii), on the basis of the matched pairs test and is rejected for treatment UNK1 on the basis of both the matched pairs test and the Fisher sign test. The linear model does not fare as well as in experiment A. Risk neutral behavior is rejected for treatments KN3 and UNK3 on the basis of both statistical tests and is rejected for treatment UNK1 on the basis of the matched pairs test. Although these results would suggest some behavioral differences between experiments A and B, as noted above such differences are not manifested by differences in overall success ratios.

In Table 9 we report the p values corresponding to the Kolmogorov Smirnov goodness-of-fit test. The empirical distributions of search terminations are tested against the risk neutral distributions of search terminations conditional on the draws. This is an approximate test since the distributions are discrete. For experiment A, neither the concave model nor the linear model would be rejected for any treatment at conventional levels of significance. In the case of experiment B, only the concave model for treatment UNK1 would be rejected. As discussed above, the concave model for UNK1 would also be rejected on the basis of both the parametric and nonparametric means tests.

Since our experimental design uses each subject as his or her own control, the offers generated within an experiment vary across treatments for each subject. Therefore, we cannot compare behavioral differences between two treatments that utilize identical draws. Our statistical tests for treatment effects are based on comparisons between selected pairs of treatments with respect to whether or not there are statistically significant differences

Table 10. Mean/median search duration tests for treatment effects—p values.

Comparison	$H_0 : E(\bar{D}^i - \bar{D}^j) = 0$ Matched pairs test ($N = 60$)	$H_0 : E(\bar{D}^i - \bar{D}^j) = 0$ Fisher sign test	$H_0 : E(\bar{D}^{in} - \bar{D}^{jn}) = 0$ Matched pairs test ($N = 60$)	$H_0 : E(\bar{D}^{in} - \bar{D}^{jn}) = 0$ Fisher sign test
Return to baseline				
UNK4(i)/UNK4(ii)	0.696	0.492 ($N = 53$)	0.724	0.789 ($N = 56$)
KN1(i)/KN1(ii)	0.070	0.096 ($N = 52$)	0.546	0.586 ($N = 54$)
Known dist. vs unknown dist.				
KN4/UNK4(i)	0.613	0.396 ($N = 50$)	0.361	0.327 ($N = 51$)
KN4/UNK4(ii)	0.312	0.166 ($N = 46$)	0.576	0.680 ($N = 53$)
KN2/UNK2	0.496	0.763 ($N = 44$)	0.269	0.149 ($N = 48$)
KN1(i)/UNK1	0.223	0.189 ($N = 47$)	0.134	0.149 ($N = 48$)
KN1(ii)/UNK1	0.369	0.199 ($N = 49$)	0.437	0.327 ($N = 51$)
KN3/UNK3	0.854	0.274 ($N = 41$)	0.503	0.668 ($N = 49$)
Reservation wage vs no reservation wage				
UNK2/UNK4(i)	0.393	0.039 ($N = 53$)	0.118	0.043 ($N = 55$)
UNK2/UNK4(ii)	0.139	0.157 ($N = 50$)	0.152	0.123 ($N = 51$)
UNK1/UNK3	0.791	0.307 ($N = 47$)	0.069	0.027 ($N = 52$)

between observed differences and theoretically-predicted differences in search durations, *conditional upon the draws*. In this case we are testing whether the behavioral treatment effects differ significantly from the theoretical treatment effects, given the draws. This methodology has been used in analysis of data from other search experiments (Cox and Oaxaca, 1989, 1992a, 1992b, 1996).

To set the stage for the "difference in difference" comparisons, we have separately tested for differences in observed behavior between treatments and for differences in predicted behavior between treatments conditional upon the draws. The results of the parametric and nonparametric tests are reported as p values in Table 10. The first comparison is for return to baseline. For experiment A there was no statistically significant difference in observed mean search duration for the UNK4 baseline treatments. Given the actual draws, theory predicted that there would be no statistically significant difference in mean search duration for the baseline treatments. In the case of experiment B, observed behavior for the KN1 baseline treatments was statistically significant, though theory did not predict such a difference, given the draws. We next examine comparisons between the known distribution treatments and the parallel unknown distribution treatments. Without exception there were no statistically significant observed differences between treatments and none were predicted conditional on the draws. On the other hand, comparisons between the reservation wage treatments and the non-reservation wage treatments yielded somewhat mixed results. According to the matched pairs test, there was no statistically significant difference in the mean durations

Table 11. Mean/median search duration tests for treatment effects—p values.

Comparison	$H_0 : E(\bar{D}^i - \bar{D}^j) - E(\bar{D}^{in} - \bar{D}^{jn}) = 0$	
	Matched pairs test ($N = 60$)	Fisher sign test
Return to baseline		
UNK4(i)/UNK4(ii)	0.306	0.384 ($N = 33$)
KN1(i)/KN1(ii)	0.049	0.695 ($N = 26$)
Known dist. vs unknown dist.		
KN4/UNK4(i)	0.741	0.353 ($N = 29$)
KN4/UNK4(ii)	0.561	0.999 ($N = 26$)
KN2/UNK2	0.050	0.048 ($N = 31$)
KN1(i)/UNK1	0.761	0.194 ($N = 29$)
KN1(ii)/UNK1	0.006	0.064 ($N = 24$)
KN3/UNK3	0.422	0.289 ($N = 32$)
Reservation wage vs no reservation wage		
UNK2/UNK4(i)	0.367	0.411 ($N = 37$)
UNK2/UNK4(ii)	0.913	0.480 ($N = 32$)
UNK1/UNK3	0.003	0.005 ($N = 29$)

for the UNK2 and UNK4(i) treatments, and none was predicted conditional on the draws. Yet according to the Fisher sign test, the difference in the observed mean durations is statistically significant and theory predicts a statistically significant difference, given the draws. Therefore, regardless of the test used observed behavioral and predicted behavioral differences are in agreement. In the case of the UNK2 and UNK4(ii) treatments, observed mean search durations were not significantly different, nor did theory predict a statistically significant difference in mean search duration conditional on the draws. Finally, when comparing behavior for the UNK1 treatment with that of the UNK3 treatment we see that the difference in observed mean search durations was not statistically significant, though theory predicted a statistically significant difference.

Table 11 presents the p values for the parametric and nonparametric tests for treatment effects in which we ask if the observed differences in treatment are significantly different from the predicted differences conditional on the draws. The first comparison is for return to baseline; this is a check to see whether learning or sequencing effects might be confounded with treatment effects in the data. In experiment A, the baseline treatments were UNK4(i) and UNK4(ii). Both the parametric and nonparametric test results (relatively high p values) indicate that the mean observed difference in search durations and the predicted mean difference are not significantly different from one another. This finding is consistent with the chi-square contingency table tests discussed above in terms of success ratios. We conclude that the subjects did return to baseline behavior in experiment A; hence learning and sequencing effects are not confounded with treatment effects in this experiment.

In experiment B, the baseline treatments were KN1(i) and KN1(ii). The parametric test indicates that the mean observed difference in search durations and the predicted mean difference are significantly different from one another. This would indicate that there is not a return to baseline. Yet the nonparametric test indicates that the observed difference and the predicted difference are not significantly different from one another. This would indicate that there was a return to baseline. The chi-square contingency table tests discussed above in terms of success ratio supports the inferences from the parametric test that there was no return to baseline in experiment B. Hence the results are somewhat mixed for experiment B, but they tend to support the conclusion that there was no return to baseline in this experiment; hence treatment effects may be confounded with learning or sequencing effects in the data for this experiment.

We next turn to the treatment effects pertaining to known versus unknown distributions. This is a check to see whether observed search behavior tracks predicted behavior with this change in the information environment. The experimental treatments with unknown distributions were designed so that their a priori probability distributions of wage offers are the same as the wage offer distribution in the paired known distribution treatment. Accordingly, the statistical comparisons here are between the appropriately paired KN*i*/UNK*i* treatments. With only two exceptions, the *p* values indicate that mean observed differences in search durations and predicted mean differences are not significantly different from one another. The exceptions are for the KN2/UNK2 and KN1(ii)/UNK1 comparisons. Both the parametric and nonparametric tests indicate that the mean observed duration difference and the predicted mean duration difference are significantly different from one another. Therefore, these are the only pairings of KN/UNK treatments in which there is evidence of a treatment effect from knowing the offer distribution as opposed to not knowing the offer distribution until an informative draw occurs.

Finally, we are interested in comparisons between treatments in which the reservation wage property exists and those in which the reservation wage property does not exist. This is an examination of a central question of whether observed search behavior tracks the non-intuitive theoretical implications of the absence of the reservation wage property. In other words, do the subjects accept and reject wage offers in ways that are consistent with optimal search in both environments with and without the reservation wage property? In the context of our experimental design, the reservation wage property is tested as a treatment effect. In experiment A, the reservation wage property does not exist for the baseline treatments, UNK4(i) and UNK4(ii), but does exist for the UNK2 treatment. In experiment B, the reservation wage property does not exist for the UNK3 treatment but does exist for the UNK1 treatment.

The *p* values from the tests for significance of the reservation wage property are reported in Table 11. For the UNK2/UNK4(i) and UNK2/UNK4(ii) comparisons in experiment A, both the parametric and nonparametric tests indicate that the mean observed search duration differences and the predicted mean differences are not significantly different from one another. For the UNK1/UNK3 comparison in experiment B, both the parametric and nonparametric test results indicate that the mean observed difference in search durations and the predicted mean difference are significantly different from one another. Only in this last comparison do the results imply a behavioral inconsistency with the predicted reservation

Table 12. Consistent searches from the unknown distribution treatments.

	Concave model				Linear model			
	Revealed		Not revealed		Revealed		Not revealed	
Treatment	Ratio	(%)	Ratio	(%)	Ratio	(%)	Ratio	(%)
Experiment A								
UNK4(i)	168/183	91.8	9/9	100.0	156/183	85.2	9/9	100.0
UNK2	126/133	94.7	75/79	94.9	116/133	87.2	66/79	83.5
UNK4(ii)	167/171	97.7	11/11	100.0	157/171	91.8	10/11	90.9
Total A	461/487	94.7	95/99	96.0	429/487	88.1	85/99	85.9
Experiment B								
UNK1	74/77	96.1	106/115	92.2	68/77	88.3	104/115	90.4
UNK3	138/141	97.9	44/44	100.0	131/141	92.9	38/44	86.4
Total B	212/218	97.2	150/159	94.3	199/218	91.3	142/159	89.3
Total A and B	673/705	95.5	245/258	95.0	628/705	89.1	227/258	88.0

wage treatment effect. That is to say, the mean observed difference in search durations as between treatments corresponding to the presence and absence of the reservation wage property is significantly different from the risk neutral model's prediction of the mean difference in search duration conditional on the actual draws.

A natural question that arises with respect to the UNK treatments is how much different is search behavior when the distribution is revealed compared to when the distribution is not revealed. In Table 12, we report the conditional success ratios for searches following a revealing draw and searches during which a revealing draw was not received. First consider experiment A. There were a total of 192 subject searches/draws in treatment UNK4(i). Of these, 183 were draws for which the distribution was revealed and 9 were draws for which the distribution was not revealed. Of the 183 searches for which the distribution was revealed, 91.8% (168) were consistent with the concave model, and 85.2% (156) were consistent with the linear model. All of the 9 searches for which the distribution was not revealed were consistent with both the linear and the concave models. Of the 182 subject searches/draws in treatment UNK4(ii), 171 were draws for which the distribution was revealed and 11 were draws for which the distribution was not revealed. Conditional upon searching when the distribution was revealed, the consistency rate was 97.7% for the concave model and 91.8% for the linear model. Conditional upon searching when the distribution was not revealed, the consistency rate was 100.0% for the concave model and 90.1% for the linear model.

In the UNK2 treatment, the probability of a revealing draw is one-half that of the corresponding probability for the UNK4 treatments. Consistent with this is the fact that 62.7% of the observed draws from the UNK2 treatment corresponded to searches in which the offer distribution was revealed compared to 94.7% for the UNK4 treatments. When the distribution was revealed in the UNK2 treatment, the consistency rates were 94.7% for the concave model and 87.2% for the linear model. Conditional on searching when the distribution was not revealed, the consistency rates were 94.9% for the concave model and 83.5% for the linear model.

There is no discernible pattern of behavioral differences in experiment A between searches when the distribution was revealed and when it was not. The overall consistency rates in experiment A for the concave model were 94.7% when the distribution was revealed and 96.0% when it was not. The corresponding percentages for the linear model were 88.1% and 85.9%. These are fairly modest differences. The overall results for experiment B are qualitatively much the same as those found in experiment A. In experiment B the overall consistency rates for the concave model were 97.2% when the distribution was revealed and 94.3% when it was not. The corresponding percentages for the linear model were 91.3% and 89.3%. It appears that knowing the distribution from which one is obtaining offers has little effect on how well the models perform.

7. Concluding remarks

The central research questions addressed in this paper are whether or not the broad consistency of earlier search experiments with the predictions of search theory carry over to search from unknown distributions, and whether or not failure or success of search theory is dependent on the existence or nonexistence of the reservation wage property. The answer to the first question is that the predictions of search theory continue to hold up remarkably well when search is from an unknown distribution. This is in spite of the fact that the overall success rates are slightly lower than in previous experiments.

The second research question is whether the empirical success or failure of search theory is dependent upon whether or not the reservation wage property exists. We address this question using search duration data. In earlier papers (Cox and Oaxaca, 1992a, 1992b), we reported experiments with known wage offer distributions in which reservation wages were observable because subjects were made to precommit to a minimally acceptable wage offer in advance of each draw from the wage offers distribution. This approach cannot be used in the present environment because a precommitment requirement precludes subjects from doing the Bayesian updating that theory requires for informative draws from an unknown distribution.

Our findings show that the success or failure of the theory is not conditioned by the presence or absence of the reservation wage property in experiment A. This conclusion is based on comparisons between search from the unknown distribution in which the reservation wage property is absent, with search from the unknown distribution is which the reservation wage property is present. Although the success rate is higher for the distribution *without* the reservation wage property (especially for the linear model), our statistical tests indicate that the observed differences in search duration between the trials with the two unknown distributions are not significantly different from the theoretically-predicted differences.

On the other hand, the results from experiment B would seem to indicate that the presence or absence of the reservation wage property affects the success or failure of the theory. Here we again compare search from an unknown distribution in which the reservation property exists with search from an unknown distribution in which the reservation wage property does not exist. The difference in success rates between trials with the two distributions are significant for the concave model but not the linear model. Our statistical tests indicate that the difference in the observed mean duration of search between trials with the two unknown distributions is significantly different from the theoretically-predicted difference in mean search duration.

We believe that we can resolve the seemingly conflicting advice from experiments A and B as to whether or not the success or failure of search theory is conditioned by the presence or absence of the reservation wage property. First, note that the reservation wage property does not vanish until period 10 in the no-reservation-wage treatment of experiment B. Since, in those trials, all searches terminated by the end of period 9 (the median and mean durations of search were 2.0 and 3.1, respectively), there was no opportunity to observe draws that would distinguish between search in the absence of the reservation wage property and search in the presence of the reservation wage property. On the other hand, the reservation wage property is absent from the very first period of the search horizon in the no-reservation-wage treatment in experiment A. Second, the statistical evidence shows a return to baseline behavior in experiment A, but the evidence is ambiguous for experiment B. Accordingly, there is some ambiguity about interpretation of the treatment comparisons from experiment B. We therefore base our inferences about the conditioning effect of the presence or absence of the reservation wage property on statistical evidence from experiment A. Our conclusion is that the success or failure of the theory is not affected by the presence or absence of the reservation wage property.

Appendix

The appendix to this paper is available upon request from the authors.

Acknowledgments

We are grateful to an anonymous referee for helpful comments and suggestions and to the National Science Foundation for financial support. Capable research assistance was provided by Lucy Atkinson Eldridge, Yvonne Durham, and Zeynep Hansen.

Note

1. The Fisher sign test may be used as a test of medians if the distributions of the random variables are not symmetric. For ease of exposition we refer to "means" in discussing parametric and nonparametric tests of central tendency.

References

Braunstein, Y. and Schotter, A. (1981). "Economic Search: An Experimental Study." *Economic Inquiry*. 19, 1–25.

Braunstein, Y. and Schotter, A. (1982). "Labor Market Search: An Experimental Study." *Economic Inquiry*. 20, 133–44.

Cox, J. and Oaxaca, R. (1989). "Laboratory Experiments with a Finite Horizon Job Search Model." *Journal of Risk and Uncertainty*. 2, 301–29.

Cox, J. and Oaxaca, R. (1992a) "Tests for a Reservation Wage Effect." In J. Geweke (ed.), *Decision Making under Risk and Uncertainty: New Models and Empirical Findings.* Kluwer Academic Publishers, Dordrecht.

Cox, J. and Oaxaca, R. (1992b). "Direct Tests of the Reservation Wage Property." *Economic Journal*. 102, 1423–32.

Cox, J. and Oaxaca, R. (1996). “Testing Job Search Models: The Laboratory Approach.” In S. Polachek (ed.), *Research in Labor Economics*, Vol. 15. JAI Press, Greenwich.

Devine, T. and Kiefer, N. (1991). *Empirical Labor Economics: The Search Approach.* Oxford University Press, New York.

Grether, D., Schwartz, A., and Wilde, L. (1988). “Uncertainty and Shopping Behaviour: An Experimental Analysis.” *Review of Economic Studies.* 55, 323–42.

Harrison, G. and Morgan, P. (1990). “Search Intensity in Experiments.” *Economic Journal.* 100, 478–86.

Hey, J. (1982). “Search for Rules for Search.” *Journal of Economic Behavior and Organization.* 3, 65–81.

Hey, J. (1987). “Still Searching.” *Journal of Economic Behavior and Organization.* 8, 137–44.

Kogut, C. (1992). “Recall in Consumer Search.” *Journal of Economic Behavior and Organization.* 17, 141–51.