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Three heuristics of search for a low price when initial information about the market is obsolete

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Three heuristics of search for a low price when initial information about the market is obsolete

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Abstract:
In traditional economics, buyer behaviour is usually modelled under the assumption of full information either on prices and their locations within the market or at least on the probability distribution of prices in the market. Neither of these assumptions seems appropriate in some cases such as when the buyer enters the specific market only very infrequently (e.g., markets for durables). This paper studies experimentally the search rules that buyers might use in this case of extreme lack of information on prices. The paper identifies three general search heuristics, derives three specific rules from the heuristics and, using data from a small-scale experiment, estimates parameters of the rules.

Keywords: search, heuristics, aspiration level, experiment

JEL: D12, D83

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I. Introduction

The subject of inquiry in this paper is the behaviour of a buyer searching for a low price in a market when s/he does not know exactly what price is charged in what shop. Specific emphasis will be put on the case when the buyer enters a market in which s/he has not been for a long time. We find ourselves in such situations more often than one might think. Looking for a job, for a firm to thoroughly renovate our house, for legal advice, selling our house or car, buying a holiday trip or a special drug - in many such situations we enter a market that we know very little about because we were there quite some time ago (if ever) so that either absolute prices in the market or relative prices among shops or both are likely to have changed in the meantime. The study of these cases seems quite relevant - many of them appear to be among the most important economic decisions we make in our lives.

Search for a low price (or a high wage) in a market where the prices differ among shops and where the buyer does not know which shop offers which price, is a phenomenon studied by economists from various angles for more than three decades. Only a fraction of this literature, however, has been devoted to the empirical study of the actual behaviour of buyers, mostly focusing on the informationally unique case of a fully known price distribution. A handful of papers, however, do try to find out what strategies people use when entering a market about which they know little.

The present paper builds on this latter stream of research and tries to add to it on both a conceptional level and an empirical level. On the conceptional level, the paper formulates three general heuristics of search which are sensitive to all the pieces of information which it seems reasonable to use. The general nature of the heuristics indicates the possibility that different buyers may either use different general heuristics in the form of completely different concrete search rules, or they may use the same general heuristic but still in the form of somewhat different concrete search rules. On the empirical level, the paper estimates three concrete search rules which are obtained as specifications of the three general heuristics. The estimation is based on data from a small-scale experiment.

Most of us probably rarely (re)enter a market while knowing absolutely nothing about it. We usually remember some of the prices we saw there in the past, have some impression of price changes which have taken place since then or we have some social network or other information sources which we can use to ask about these basic facts before we (re)enter the market. This is why this paper focuses on the case where there are two at least very weakly useful pieces of information: an old price (the price seen in the market in the past by the buyer or by the people s/he asks) and a prediction of how much the prices are likely to have generally changed since the time the old price was valid.

The paper is structured as follows. In Section II the relevant literature within economics, psychology and marketing research is briefly overviewed. Section III identifies three general search heuristics and, on their basis, three rules whose parameter values will be estimated using data obtained in a small-scale experiment conducted for that purpose. The experiment is described in Section IV. In Section V, results of the estimation are reported and the three rules are compared as to how well each of them corresponds to the data. Section VI concludes by sketching ways for future research.

II. Relevant literature

When looking for findings on the actual behaviour of a buyer who searches for a low price in a little-known market, it seems natural to look into three disciplines: economics, psychology and marketing studies.

In economics, the phenomenon of price search has been studied mostly using three basic approaches: theory-building, simulation and observation.[1] By theory-building we mean mathematical derivation of the optimum search rule appropriate to the assumed situation. "Search rule" or just "rule" refers in the search literature to the way the searcher decides at each moment during his/her search whether to stop the search or not. "Optimum search rule appropriate to the assumed situation" is then any rule which, if used by the searcher in the assumed situation, leads to maximizing the expected value of his/her assumed objective function.

Probably the first model of this kind is contained in the appendix of the classic article by Simon (1955). It was Stigler (1961, 1962) and McCall (1965), however, who were successful in bringing this topic to the attention of economists (for a survey, see McMillan & Rothschild, 1994, and Eckstein & van den Berg, 2003). As regards the way buyers actually reason, this approach - with its emphasis on optimal rather than actual search strategies - obviously has little to say.

[1] Implicitly it will be assumed throughout this paper that there is no structure in the set of options (here prices) that the searching individual browses. Examples of papers in which such structure is assumed are Radner (1975) and Wall (1993). Also, attention in this paper will be focused on the sequential type of search which seems more suitable for studying the present subject of inquiry than the other possible type, the fixed sample size search in which the total number of stores to be visited would be determined by the buyer before s/he enters the first store.

Simulation is often used to help find out (where it is too difficult to do so analytically) what results we can expect to obtain if we use a given rule in a given situation, with various parameters and other characteristics of the rule and/or of the task taking on various values from predetermined intervals. The pioneer in using simulation was Telser (1973), followed later by Hey (1982), Dudey & Todd (2001) and others. Neither this approach in itself gives us any hints as to what rules buyers actually use when searching for a low price. We might view as candidates for actual use those rules which perform well under most realistic combinations of parameters. This approach, however, makes sense only under the assumption that some kind of evolutionary selection pressures are at work in the area of search rules used by buyers - an assumption which does not seem particularly appropriate for this area.

Observational approach seeks mainly to find out what rules people actually use in various tasks of the price-search type, or at least what properties these rules have. Several approaches in both the price search tradition and the very closely related wage search tradition can be distinguished, such as comparative statics (Butler & Loomes, 1997, Hey, 1993, Urbany, 1986), statistical regression identifying the correlates of search (Hey, 1993, Kogut, 1990) and estimation of specific search rules (Butler & Loomes, 1997, Hey, 1982, Houser & Winter, 2004, Martin & Moon, 1992, Moon & Martin, 1990, 1996, Schunk & Winter, 2005, Sonnemans, 1998, 2000; the present paper).

Findings of the observational approach within economics are directly relevant for the present subject of inquiry. Especially the studies which assume no or very limited information on the price distribution and try to estimate specific search rules (Butler & Loomes, 1997, Hey, 1982, Martin & Moon, 1992, Moon & Martin, 1990, 1996) can give us some inspiration for the identification of the heuristics and rules to be estimated in this paper. The inspiration from specific rules dealt with in specific papers will be mentioned later on when we spell out individual search heuristics.

In psychology, search for a low price would be considered to belong to the family of tasks usually labeled as “optional stopping” (e.g., Corbin *et al.*, 1975, Seale & Rapoport, 1981, Zwick *et al*., 2003). Most optional-stopping studies, however, focus on the case where the searcher monitors only the relative rank of the observations encountered so far. This focus on ranks is perfectly appropriate in situations (such as the usually mentioned case of search for as new secretary) where the precise quantitative values of the options are hard to determine and only the rank order of the options is relevant. In the present setup, however, the focus only on ranks of the price quotes encountered would seem to be somewhat unrealistic.

Not surprisingly, we can find a number of papers more or less related to the issue of search for a low price in the marketing literature (e.g., Beatty & Smith, 1987, Moorthy, Ratchford & Talukdar, 1997, Urbany, 1986). Most of these papers are limited, however, to identification of correlates of search effort or look at the issue from other perspectives and do not try to answer the specific question of what particular strategies buyers use to find a low price.

III. Assumptions and Hypothesis

Search conducted by buyers in a little-known market will be studied here by assessing the extent to which data collected in an experiment we conducted support the hypothesis that buyers in such a situation search for a low price according to one of several rules. Before identifying the rules to be tested, in order to make the topic tractable and to focus on the search aspect of the buyer behaviour, let’s introduce several simplifying assumptions on the searcher’s motivation and on the whole situation in which s/he searches:

1) The buyer will be assumed to perceive a need of a constant intensity to get exactly one unit of a single good. S/he does not have to determine which goods and how much of each of them to buy and under what conditions to leave the market without buying the good.

2) The buyer will be assumed to expect the overall price distribution in the market not to change to any considerable degree between the beginning and the end of his/her present search. Otherwise the consumer would have to be prepared to solve the formidable task of forming an idea not only about the price distribution but also about its rate of change in time.

3) Each of the shops inspected will be assumed to offer the same single brand of the good and thus exactly one price can be observed in each shop; "observing a price" then corresponds to "inspecting a shop".

4) Apart from the price observed to be charged in a given shop for one unit of the good, the first or any further inspection of any of the shops will be assumed to have about the same characteristics for the buyer as the first or any further inspection of any other shop.

5) Each of the prices that the buyer has seen during his/her present search will be assumed to remain the same and available for him/her to return to the shop where s/he saw the price and buy the good at that price if s/he chooses to do so at any moment later during the search.

6) The buyer will be assumed to know at the beginning of his/her search all facts describing the situation in which s/he searches except the price distribution and the concrete prices s/he is going to encounter in various shops during his/her search. The facts which describe the situation and which the buyer is aware of, include

a) the "old price", the price that the buyer remembers from his/her previous exposure to the market (alternatively, the price his/her friends or relatives say they encountered the last time they were in the market),

b) the "prediction", a rough idea of the change in the overall price level that has taken place since the last time the buyer was in the market (e.g., based on information from experts talking in the media about inflation),

c) the "search cost", the value of an aggregate measure of amounts of various resources that the buyer has to give up and amounts of various sufferings s/he has to undergo to inspect any single shop without owning the good yet. Assumptions 1) and 4) above imply that this search cost is the same for all shops, including those to which the buyer would return.

We can now turn to the identification of relevant general search heuristics and then specific search rules to be estimated. We will attempt to apply to the present context a modest version of the ex ante methodological assumption that underlies most models of decision-making in economics, namely, of the assumption of (evolved) rationality. More specifically, we will concentrate on those heuristics and rules that follow certain intuitive logic (regardless of the implied computational simplicity or complexity) which gives a promise that the heuristic or rule tends to avoid inefficient search.[2] This includes the assumption that the rules do not waste information: they allow for the use of all data which it might be reasonable to use in that situation, i.e., any piece of information such that ignoring that piece could in some circumstances lead to an extremely inefficient search. This version of rationality is modest in the sense that the rules need not be optimal. All we require is that promise to avoid grossly inefficient search.

The empirical literature on search in a little-known market has already suggested quite a few rules (a useful list is provided in Houser & Winter, 2004). Through some of these rules, summarised in Table 1, three different general search heuristics transpire which can be considered reasonable in the above sense.

[2] We thus do not consider, for example, the possibility that buyers might proceed by taking first a limited sample from the distribution and then waiting for a quote which will exceed the best quote in the sample. This search behaviour is very simple and may have near-optimal properties (as shown by simulations in Todd, 1997) but it does not use all information which it might be reasonable to use in the present context and it does not appear to be based on any intuitive logic (the fact that such a rule gives quite good results comes rahter as a surprise).

Table 1: Search rules identified in previous research and related to one of the three rules tested here

source	label	rule
Butler, Loomes (1997), p. 133	-	"Set some initial aspiration level and begin to search. After each quote, modify aspirations to take account of the quote(s) obtained so far. Continue searching until you have received a quote that allows you to do as well or better than your current aspiration level."
Moon & Martin (1990), p. 182	K	"Keep searching until a price is found at least one standard deviation below the mean, up to a maximum of σ/c searches (rounded)." (σ is the standard deviation of the known price distribution, c is the search cost)
Moon & Martin (1990), p. 183	K*	"Keep searching until a price is found at least 0.75 standard deviations below the mean, up to a maximum of σ/c searches (rounded)."
Martin & Moon (1992), p. 260	T	"Keep searching until a price, p, is located such that $p \leq 90\%\ m$, but with a maximum search cost of 10% m, unless minimum $p > m + c$." (m is average of all prices so far received)

Each of these three heuristics determines the reservation price d^*_t, that is, a price such that at time t, the buyer using the heuristic considers that price or any lower price to be acceptable and any higher price inacceptable. Labelling the search cost expressed in monetary terms as c, the buyer who follows a given heuristic will agree to buy the good at time t at the price $p_{mt} \equiv min\{p_1 + c, p_2 + c, ..., p_{t-1} + c, p_t\}$ iff $p_{mt} \leq d^*_t$. The three general heuristics will be called Adaptation Heuristic, Bargain Heuristic and Improvement Heuristic.

Adaptation Heuristic (see the rule suggested in Butler & Loomes, 1997): After observing p_t, the buyer adapts his/her reservation price from its previous value d^*_{t-1} to d^*_t that seems to his/her appropriate in view of the newly observed price. S/he sets d^*_t somewhere in between d^*_{t-1} and p_t.

Bargain Heuristic (see rules K, K* in Moon & Martin, 1990, and the first part of rule T in Martin & Moon, 1992): After observing p_t, the buyer considers all data which s/he considers relevant and which are available to him/her at the moment and s/he decides how much below the average of the prices being offered in the market - whose value s/he must somehow estimate - s/he will set d^*_t so that s/he can consider it a bargain price.

Improvement Heuristic (see the last part of rule T in Martin & Moon, 1992): After observing p_t, the buyer considers the improvement which is likely to be brought about by the next search step. S/he considers p_{t+1} - whose value s/he must somehow predict - worth inspecting only if s/he expects it be lower than p_{mt} by more than the search cost of the step leading to inspection of p_{t+1}. That is, d^*_t is equal to an estimate of the next price increased by c.

These three heuristics are sufficiently general to serve as bases for search rules in many types of search situations. On the other hand, they are too general to be used directly to guide the search in any particular situation - we need to determine exactly how the searcher uses - within a given heuristic - the information that is available in the specific search context at hand. The three rules that appear below are derived from the heuristics by suggesting, for each heuristic, one - admittedly not the only one - possible way to "fill" it with information that it would be reasonable to use in the particular situation of buying in a little-known market (in other particular search contexts with a different volume or structure of information, the heuristics might imply somewhat differently phrased search rules). What is this information?

When, at the end of each search step, making the decision whether to go on searching or to terminate the search, the buyer would certainly be reasonable to compare in some way - even if unconsciously or in a very simple way - the prices that s/he thinks the market offers and the costs of inspecting various shops in an effort to locate a price that is relatively low among the prices s/he considers available. Obviously, ignoring what the prices in the market may look like and determining the length of search solely on the basis of the costs of search may lead the buyer to search far too little or far too much relative to what prices are actually available in the market, and the same applies to ignoring the costs and focusing only on the prices that the market offers (as in some of the rules suggested, e.g., byHey, 1982).

When (re-)forming at each moment of the search his/her idea of the prices that the market offers, the buyer would certainly be reasonable to take into account (unlike some of the rules suggested, e.g., by Hey, 1982, Moon & Martin, 1990, and Martin & Moon, 1996) all prices seen so far during the present search - the prices s/he has so far observed during the present search are the only direct and thus the most valuable piece of information on what the whole price distribution actually looks like.

Assumption 6) offers two other sources of information which the buyer could use when s/he (re-)forms his/her idea on what the prices in the market may look like - namely, the old price and the prediction. These data, however, give indirect information only and thus it is a matter of personal opinion and momentary circumstances whether it is reasonable to use them during the search. Generally speaking, for different buyers, to use these two sources of information may be reasonable to a different extent (including no extent at all).

As to the search cost of a given search step, it is an aggregate of several variables. Some of them are the opportunity costs of search implied by the several budget constraints (time, money, physical energy, etc.) that every buyer faces and within which s/he must conduct the present search side by side with all his/her other activities. In addition, there is usually an element of time discounting (e.g., the suffering that the buyer has to undergo when s/he is to do without the good for the present time period). There is no reason to distinguish among the various types of search cost as to how reasonable it is for the buyer to take them into consideration - neglecting any of them may lead to a huge gap between what the search takes and what it brings.

As regards the particular search steps whose costs should be taken into account at a given point during the search, it is sure that the cost of the very next search step should be considered because if its value is very extreme relative to what prices the buyer thinks are available in the market, s/he can make an easy decision. But apart from this, there seems to be no persuasive general argument for either excluding or including the other search steps' costs. When specifying the rules to be tested, simplicity suggests that we should include in the rules the cost of the next search step only (or the average of all search steps, because these two values will - for a constant search cost - be equal).

To sum up, we suggest that the use of the following four types of information might be reasonable:

(1) all prices seen so far,

(2) the cost of the next search step;

and the following kinds of information were identified as reasonable to be used under some circumstances or in the opinion of some buyers:

(3) the old price,

(4) the prediction.

We suggest that when looking for search rules as specifications of the above three general search heuristics for the case of a little-known market on which we focus in this paper, all the four types of information that we just listed should have a chance to play a role in such search rules. One possible way to do this for each heuristic is captured in the following triad of search rules which we will call Adaptation Rule, Bargain Rule and Improvement Rule.

Adaptation Rule: $d^*_t \equiv d^*_{t\text{-}1} + \{1 - (c_{min}/c)^{\delta}\}(p_t - d^*_{t\text{-}1})$, where $d^*_0 = \{1 - \phi\}p_0 + \phi(1 + \pi/100)p_0$,

$\delta > 0$, c_{min} is the lowest possible value of c, $0 \leq \phi \leq 1$.

In accord with what was said above about the possibility (but not necessity) of buyers taking into account the prediction π, it is assumed that the prediction may play a role. In particular, the initial idea d_0 of an acceptable price is assumed to be equal to a weighted average of (1) the old price p_0 and a (2) the price that we obtain when the prediction π (whose format is, e.g., "20%") is applied to the old price.

c_{min} is a constant whose value is arbitrary except that it should not be higher than the lower boundary of the range of plausible values of c. The role of c_{min} is just supporting - it helps to form the ratio c_{min}/c such that the value of $1 - (c_{min}/c)^{\delta}$ is an increasing function of c and that is between 0 and 1 for any $c \geq c_{min}$ and any $\delta > 0$, as is required if the adaptation is always to be stronger for higher c and if it is to lead to d_t located between d^*_{t-1} and p_t. Obviously, if we change c_{min}, the value of δ changes appropriately.

Bargain Rule: $d^*_t \equiv \{1 - [(c_{min}/c)(V_t/V_{max})]^{\alpha}\}E_t$,

where $\alpha > 0$, $\beta \geq 0$, $\gamma \geq 0$,

$V_{max} \geq V_t = \Sigma_1^t (p_t - E_t)^2/t$,

$E_t = \{1 - [t/(t + 1)]^{\beta}\}p_0 +$

$+ [t/(t + 1)]^{\beta}\{\{1 - [t/(t + 1)]^{\gamma}\}(1 + \pi/100)p_0 + [t/(t + 1)]^{\gamma}M_t\}$.

Here d^*_t is the price that the buyer views at time t as a bargain. The distance in which d^*_t lies below the buyer's idea of the average price E_t in the market is assumed to be the larger, (a) the larger is the buyer's idea V_t of the spread of the prices in the market (because with this spread getting larger, the likelihood increases that a very low price will be found), and (b) the smaller is the cost c of search (because with this cost falling, waiting to encounter a given bargain price gets less expensive).

V_t is assumed to be equal to the variance of all the prices the buyer has seen so far during the search. This variance is calculated around E_t. V_{max} is a constant whose value is arbitrary except that it should not be lower than the upper boundary of the range of plausible values of V_t.

The role of both c_{min} and V_{max} is again just supporting - they are used in the Bargain Rule just to make sure that the coefficient by which E_t is multiplied is an increasing (decreasing) function of c (of V_t) and that the coefficient stays between 0 and 1 for any $c \geq c_{min}$, $0 \leq V_t \leq V_{max}$, $\alpha > 0$. Similarly to the impact of c_{min} in the Adaptation Rule, the value of α depends on how we choose the value of the ratio c_{min}/V_{max}.

Again in accord with what was said above, π and p_0 are assumed to possibly enter the buyer's thinking, but this time they take part in the estimation of the average of prices available in the market. In particular, the estimate E_t of the average of prices available in the market is assumed to be calculated as a weighted average of the old price p_0 and a weighted average of (1) the price that we obtain when the prediction p is applied to the old price, and (2) the average M_t of prices seen so far during the search. The weights of both p_0 and π are assumed to decrease in time - in other words, as the search proceeds the old price and the prediction are assumed to lose their impact on the buyer's idea of what the prices in the market may look like and this idea is more and more based just on the prices actually observed during the search.

Improvement Rule: $d^*_t \equiv E_t + c$.

The way the buyer predicts the value of p_{t+1} is assumed to be identical with the way s/he estimates the average price in the market, i.e., it is assumed that s/he predicts p_{t+1} to be equal to E_t.

The hypothesis is then threefold: individuals searching for a low price search according to the Adaptation Rule / Bargain Rule / Improvement Rule.

IV. Design and Implementation of the Experiment

In the instructions for the experiment, each subject was asked to imagine that s/he wants to buy one unit of a good ("first run") and then one unit of another good ("second run"). The goods were described as good S and good T to avoid any real-life connotations. In each run, the subject could see up to eight different prices of the good in question, each price written on a paper card turned the price-side down so that it had to be turned over to see the price. Each time the subject turned a card over, s/he had to pay a "travel fee". After seeing the price on the card, the subject had to turn the card into the original position. If s/he decided to buy at a price already passed, s/he had to pay the travel fee too because s/he had to re-visit that shop. The maximum number of eight quotes was selected so as to exceed the number of quotes we care to collect in most real-life consumer search situations (perhaps except in rare cases where the prices differ a lot and search costs are minuscule).

At the beginning of each run, the subject was also told the value of the initial endowment that was reserved for his/her expenses in that run (both for travel fees and for the price eventually paid), the old price of the good s/he was to buy in that run, and the prediction of how much the general price level (for that run) might have increased since the buyer had been in the market last time.[3]

All relevant values for all 24 subjects and for both runs are shown in Table 2. For each subject, prices of one of the two goods - we can call that search the "low-price run" - were drawn from a price distribution whose mean was about four times lower than the mean of the distribution from which prices of the other good were drawn - this other search can be called

[3] In the instructions for both runs, the old price was operationalized as the price available anywhere before a price liberalization (an event which took place in the early 1990s and which many people in the Czech Republic still remember). The prediction was operationalized as the pre-liberalisation forecast given by experts in the media of the price jump due to the price liberalization.

the ”high-price run”. The means of the price distributions ranged roughly from 21 to 24 korunas or CZK for low-price searches and roughly from CZK 88 to 91 for high-price runs.[4]

Standard deviations as well as old prices for low-price runs are roughly four times lower than those for high-price runs. Endowments for high-price runs were roughly double those for low-price runs (the ratio was set lower than four to avoid excessive differences in the overall earning from the experiment). Both extremes of the range of travel costs are somewhat higher in high-price runs compared to low-price runs. Given that the focus of this paper is estimation of search rules rather than comparative-static effects of changing the levels of individal variables, values of most variables were varied across subjects within the low-price runs and also within the high-price runs.

Already when registrating for the experiment, the subjects were informed by a poster that immediately after the experiment, they would receive a turn-up fee of CZK 40 plus their earnings in the experiment (nothing was indicated to subjects about how high these earnings might be). These earnings were calculated after the experiment as the sum (rounded up to the nearest koruna) of the amounts that remained from the initial endowments for the two runs, after all travel fees that were incurred during the two runs and the prices that were paid at the end of the two runs were deducted from the initial endowments.

To prevent subjects from making an obviously erroneous purchase once they decided to buy the good and thus to save us from the theoretical analysis of the results from the need to deal with such mistakes, each subject knew that when s/he would announce that s/he wanted to buy the good, the experimenter would make him/her buy it for p_{mt}.

[4] 1 euro is equivalent to about CZK 28. Average nominal hourly wage in the Czech Republic is about CZK 110.

Table 2: Input data for each subject

first run	code	μ	s	π	p_0	N	c	code	μ	s	π	p_0	N	c
high price	M1S	21.1	3	20	16.0	55	1.50	M1T	88.1	12	20	66.5	120	2.00
low price	M2S	21.2	3	25	16.1	55	1.25	M2T	88.2	12	25	66.6	120	1.75
high price	M3S	21.3	3	30	16.2	55	1.00	M3T	88.3	12	30	66.7	120	1.50
low price	M4S	21.4	3	35	16.3	55	0.75	M4T	88.4	12	35	66.8	120	1.25
high price	M5S	21.5	3	40	16.4	55	0.50	M5T	88.5	12	40	66.9	120	1.00
low price	M6S	21.6	3	45	16.5	55	0.25	M6T	88.6	12	45	67.0	120	0.75
high price	M7S	21.7	3	50	16.6	60	1.50	M7T	88.7	12	50	67.1	120	2.00
low price	M8S	21.8	3	20	16.7	60	1.25	M8T	88.8	12	20	67.2	125	1.75
low price	M9S	21.9	3	25	16.8	60	1.00	M9T	88.9	12	25	66.5	125	1.50
high price	M10S	22.0	3	30	16.0	60	0.75	M10T	89.0	12	30	66.6	125	1.25
high price	M11S	22.1	3	35	16.1	60	0.50	M11T	89.1	12	35	66.7	125	1.00
low price	M12S	22.2	3	40	16.2	60	0.25	M12T	89.2	12	40	66.8	125	0.75
low price	R1S	23.1	3	20	16.5	60	1.00	R1T	90.1	12	20	67.1	125	1.50
low price	R2S	23.2	3	25	16.6	60	0.75	R2T	90.2	12	25	67.2	125	1.25
low price	R3S	23.3	3	30	16.7	60	0.50	R3T	90.3	12	30	66.5	125	1.00
low price	R4S	23.4	3	35	16.8	60	0.25	R4T	90.4	12	35	66.6	125	0.75
low price	R5S	23.5	3	40	16.0	60	1.50	R5T	90.5	12	40	66.7	125	2.00
low price	R6S	23.6	3	45	16.1	60	1.25	R6T	90.6	12	45	66.8	125	1.75
high price	R7S	23.7	3	50	16.2	60	1.00	R7T	90.7	12	50	66.9	125	1.50
high price	R8S	23.8	3	20	16.3	60	0.75	R8T	90.8	12	20	67.0	130	1.25
high price	R9S	23.9	3	25	16.4	60	0.50	R9T	90.9	12	25	67.1	130	1.00
high price	R10S	24.0	3	30	16.5	60	0.25	R10T	91.0	12	30	67.2	130	0.75
high price	R11S	24.1	3	35	16.6	65	1.50	R11T	91.1	12	35	66.5	130	2.00
high price	R12S	24.2	3	40	16.7	65	1.25	R12T	91.2	12	40	66.6	130	1.75

Notes: Subjects are coded M1, M2, ..., M12, R1, ..., R12.
Runs are coded: S...low price run, T...high price run.
Variables: μ ... mean of the distribution from which prices were generated
s ... standard deviation of the distribution from which prices were generated
c ... travel fee
N ... initial endowment
p_0 ... old price
π ... prediction

The prices were generated from normal distributions with their left tails truncated at the level of the corresponding old prices. All values and the order of the two runs were determined entirely independently of which subject they would apply to.

24 subjects participated in the experiment, of which 11 were women. One subject was a member of the staff of the Faculty of Social Sciences, Charles University, the others were students of the Faculty. All subjects were recruited in the same way: they read posters which were posted at several places in the main building of the Faculty, inviting them to take part in an economic experiment.

V. Results

Apart from the turn-up fee of CZK 40, the subjects earned on average CZK 75.90 in the experiment itself (SD = CZK 9.6, range CZK 53.0 ÷ CZK 92.30). The total number of shops visited and thus the total number of observations that will be analysed below was 128. If a subject returned to a previously visited shop, it was always to buy the good there, i.e., it was never just to refresh his/her memory. There were 48 runs (2 runs for each of the 24 subjects) and so the average number of shops visited per run was about 2.7. In 15 runs which will be called "single-price searches" or SPS's, just one shop was visited (see Table 3), in two runs (both by subject M6) all eight shops were visited.

Table 3: Indices of observations in which single-price searches occurred

	subject											
run	M1	M2	M4	M5	M7	M8	M9	M10	R3	R4	R7	R11
low pr.	1	3*	14*	18*		44*	46*	50	77*			
high pr.	2*			19	43*	45				85	100*	121*

Note: A star marks the first of the two runs the subject went through.

Some notation will be needed below. i = 1, 2, ..., 128 is the index of the observation (while t was used above as the index within a concrete run). The decisions of the subject will be captured by variable y_i taking on value 0 if the decision in the i-th observation was to stop and value 1 otherwise. We will assume that for the i-th observation, the subject determines d_i

and decides to stop if $d_i \geq p_{mi} \equiv min\{p_1 + c, p_2 + c, ..., p_{i-1} + c, p_i\}$ and s/he decides to go on searching if $d_i < p_{mi}$. We will model this setup with the probit technique: we will assume $d_i \sim N(d^*_i, \sigma)$, that is, $e_i \sim N(0, \sigma)$, where $e_i \equiv d_i - d^*_i$ is the deviation of the actual reservation price d_i from the suggestion d^*_i of the rule. Using label F for the cumulative normal distribution function with mean equal to 0 and standard deviation equal to 1, the above assumption implies $p(y_i = 1) \equiv p(d_i < p_{mi}) = F[(p_{mi} - d^*_i)/\sigma]$. The vector of parameters of the rule under study will be generally labelled as $\boldsymbol{\xi}$. Estimates of $\boldsymbol{\xi}$ and σ will be found through grid search aimed at maximising their joint likelihood. The resulting maximum likelihood estimates will be labelled $\boldsymbol{\xi}_{ML}$ and σ_{ML}.

There are several ways in which the goodness of fit of probit estimation can be assessed for a given rule relative to the other rules; unfortunately, none of these ways can be considered superior and decisive (Amemiya, 1981). We will report two such measures, both of which are lower for models with a better fit. One will be the percentage of wrongly predicted observations. The other one will be the sum of squared residuals weighted by estimated probabilities of both values of y_i; formally,

$$\text{WSSR} = \Sigma_i\, [y_i - F(.)_i]^2 / \{F(.)_i[1 - F(.)_i]\},$$

where $F(.)_i$ stands for $F[p_{mi} - d_i(\boldsymbol{\xi}_{ML})]$.

Unfortunately, neither of these two measures of fit allows adjustment for degrees of freedom. This is why they have to be used with caution in cases where the two rules being compared have different numbers of parameters.

Now we can turn to the actual estimates. Estimates ($\boldsymbol{\xi}_{ML}$, σ_{ML}) for each of the three rules for all 128 observations[5] obtained in the experiment together with the values of two summary measures are reported in Table 4.

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[5] Starting with estimation of the parameters of each of the three rules on all observations implies starting the whole estimation process with the implicit assumption that (a) all subjects in (b) all cases

Table 4: ML estimates for all observations and two summary measures

rule	α_{ML}	β_{ML}	γ_{ML}	δ_{ML}	ϕ_{ML}	σ_{ML}	WSSR	wrong pred.[a]
Adaptation	-	-	-	0.07	0.00	25.5	128.33	34.4% (44 obs.)
Bargain	0.32	0.02	0.06	-	-	5.2	*127.94*	*32.8% (42 obs.)*
Improvement	-	2.4	0.00	-	-	17.1	128.52	35.9% (46 obs.)

Notes: [a]Rounded percentage of wrong predictions, 100% is 128 observations.
Italics is used to emphasize that WSSR and wrong predictions can be compared directly for Adaptation Rule and Improvement Rule only, because the Bargain Rule has one parameter more than the other two rules.

Perhaps the easiest explanation for the excessively high values of σ_{ML} is that not all the decisions made by all the subjects in all the runs in the experiment are generated by the same underlying mechanism (a rule of any kind, a specific rule, a specific rule with specific parameter values). Maybe the estimates might be made more realistic and better-fitting if the whole data-set is divided according to some a priori plausible criterion and if the rules' parameters are estimated separately on the resulting subsets of observations.

One possibility is to put aside observations which we might suspect to be generated by a mechanism different from the mechanism that generated the bulk of the decisions.[6] We could probably generate several different stories, each leading us to delete a different set of observations. One simple story suggests we should get rid of the SPS's: SPS's are those searches which were terminated at the earliest possible moment. Perhaps SPS subjects formed some prior idea of the price distribution and combined it with some risk aversion, or that they had a high unobserved search cost (on top of c), or that their decision to go on or to stop was based on some relatively low aspiration level for net earnings from the experiment, etc.

This reasoning accounts fully for the behaviour of the three subjects (M1, M5 and M8) who stopped in both runs at the first price. Also the behaviour of the seven subjects who stopped in the first run at the first price but went beyond the first price in the second run is not

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use the same search rule with the same specific parameter values. Later estimations will try to relax at least part (b) of this double assumption.

[6] Obviously, there is also the possibility of separating the low-price-run data subset and high-price-run data subset further (e.g., according to various characteristics of the subjects) so that for each

hard to interpret simply and yet consistently with the above explanation: they made what they might have considered a nice sum in the first run and so maybe they thought they could afford to have some fun (and maybe earn more) by taking more risk in the second run. As for the subject R4 who saw several prices in the first run but stopped at the first price in the second run, closer look shows that we do not need any special story because this subject's SPS actually supports the Bargain Rule as it was estimated and is very close to supporting the other two rules. In other words, from the point of view of the rules, this particular SPS was a fairly reasonable thing to do and so in this case there is no strong need for an alternative explanation. Just one SPS (M10) fits none of the above stories: s/he did some search in the first (high-price) run and stopped at the very first quote in the second (low-price) run without this stopping being consistent with any of the three rules.

ML estimates of the parameter values for low price runs and high price runs separately (SPS's excluded) for the three rules are given in Table 5.

Table 5: ML estimates for low price runs only (SPS's excluded) and high price runs only (SPS's excluded) and two summary measures

low price runs only (SPS's excluded)								
rule	α_{ML}	β_{ML}	γ_{ML}	δ_{ML}	ϕ_{ML}	σ_{ML}	WSSR	wrong pred.
Adaptation	-	-	-	0.36	0.00	1.9	38.82	25.0% [a] (14 obs.)
Bargain	0.28	0.10	0.00	-	-	0.8	*47.79*	*17.9%* [a] *(10 obs.)*
Improvement	-	1.9	0.00	-	-	2.4	44.96	28.6% [a] (16 obs.)
high price runs only (SPS's excluded)								
rule	α_{ML}	β_{ML}	γ_{ML}	δ_{ML}	ϕ_{ML}	σ_{ML}	WSSR	wrong pred.
Adaptation	-	-	-	0.09	0.00	15.3	52.87	29.8% [b] (17 obs.)
Bargain	0.33	0.17	0.00	-	-	5.7	*54.69*	*24.6%* [b] *(14 obs.)*
Improvement	-	2.2	0.00	-	-	10.1	52.70	28.1% [b] (16 obs.)

Notes: [a]Rounded percentage of wrong predictions, 100% is 56 observations.
[b]Rounded percentage of wrong predictions, 100% is 57 observations.
Italics is used to emphasize that WSSR and wrong predictions can be compared directly for Adaptation Rule and Improvement Rule only, because the Bargain Rule has one parameter more than the other two rules.

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of the three rules and for each of the two levels of prices we would get several sets of parameter estimates. This direction is mentioned also in the conclusion.

The results may be summarised as follows. For both high-price and low-price runs, the WSSR score of the Bargain Rule is higher than the scores for the other rules, which speaks against the Bargain Rule. Exactly the opposite pattern holds for the proportion of wrong predictions. Apart from that, the Adaptation Rule is somewhat better than the Improvement Rule in terms of both measures for low-price runs, while for high-price runs, the two rules fare about equally well on both accounts. Below are the rules as they read with the parameter values reported in Table 5:

Adaptation Rule for low price runs:

$d^*_t \equiv d_{t-1} + \{1 - (0.05/c)^{0.36}\}(p_t - d_{t-1})$, where $d_0 = p_0$.

Adaptation Rule for high price runs:

$d^*_t \equiv d_{t-1} + \{1 - (0.05/c)^{0.09}\}(p_t - d_{t-1})$, where $d_0 = p_0$.

Bargain Rule for low price runs:

$d^*_t \equiv \{1 - [(0.05/c)(V_t/3600)]^{0.28}\}E_t$, where $E_t = \{1 - [t/(t+1)]^{0.10}\}p_0 +$

$+ [t/(t+1)]^{0.10}M_t$.

Bargain Rule for high price runs:

$d^*_t \equiv \{1 - [(0.05/c)(V_t/3600)]^{0.33}\}E_t$, where $E_t = \{1 - [t/(t+1)]^{0.17}\}p_0 +$

$+ [t/(t+1)]^{0.17}M_t$.

Improvement Rule for low price runs:

$d^*_t \equiv \{1 - [t/(t+1)]^{1.9}\}p_0 + [t/(t+1)]^{1.9}M_t + c$.

Improvement Rule for high price runs:

$d^*_t \equiv \{1 - [t/(t+1)]^{2.2}\}p_0 + [t/(t+1)]^{2.2}M_t + c$.

Tables 6 - 8 may help to get a better idea of how these rules work.

Table 6: Values (in the form of rounded percentages) of the c- and V_t-dependent coefficients appearing in the Bargain Rule

coefficient	V_t	c = 0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
$1 - [(0.05/c)(V_t/3600)]^{0.28}$	0.16[b]	4%	3%	3%	3%	2%	2%	-[a]	-[a]
$1 - [(0.05/c)(V_t/3600)]^{0.28}$	2.83[c]	9%	7%	6%	6%	5%	5%	-[a]	-[a]
$1 - [(0.05/c)(V_t/3600)]^{0.28}$	12.99[d]	13%	11%	10%	9%	8%	8%	-[a]	-[a]
$1 - [(0.05/c)(V_t/3600)]^{0.33}$	6.52[b]	-[a]	-[a]	5%	5%	4%	4%	4%	4%
$1 - [(0.05/c)(V_t/3600)]^{0.33}$	82.85[c]	-[a]	-[a]	12%	11%	10%	9%	9%	9%
$1 - [(0.05/c)(V_t/3600)]^{0.33}$	208.32[d]	-[a]	-[a]	16%	15%	13%	13%	12%	12%

Notes: [a]The value of c did not appear in the observations to which the coefficient applies.
Three values of V_t were selected at which the coefficients' values are stated:
[b]The lowest value of V_t (among all observations to which the coefficient applies) when V_t is evaluated at the ML estimates' values.
[c]The average value of V_t (over all observations to which the coefficient applies) when V_t is evaluated at the ML estimates' values.
[d]The highest value of V_t (among all observations to which the coefficient applies) when V_t is evaluated at the ML estimates' values.

Table 7: Values (in the form of rounded percentages) of the c-dependent coefficients appearing in the Adaptation Rule

coefficient	c = 0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
$1 - (0.05/c)^{0.09}$	-[a]	-[a]	22%	24%	25%	26%	27%	28%
$1 - (0.05/c)^{0.36}$	44%	56%	62%	66%	69%	71%	-[a]	-[a]

Notes: [a]The value of c did not appear in the observations to which the coefficient applies.

Table 8: Values (in the form of rounded percentages) of the t-dependent weights appearing in the Bargain Rule and in the Improvement Rule

weight	t = 1	2	3	4	5	6	7	8
$1 - [t/(t+1)]^{0.02}$	1%	0%	0%	0%	0%	0%	0%	0%
$1 - [t/(t+1)]^{0.10}$	7%	4%	3%	2%	2%	2%	1%	1%
$1 - [t/(t+1)]^{0.17}$	11%	7%	5%	4%	3%	3%	2%	2%
$1 - [t/(t+1)]^{1.9}$	73%	54%	42%	35%	29%	25%	22%	20%
$1 - [t/(t+1)]^{2.1}$	77%	57%	45%	37%	32%	28%	24%	22%
$1 - [t/(t+1)]^{2.2}$	78%	59%	47%	39%	33%	29%	25%	23%

When the estimation is conducted separately for low price runs and high price runs and after apparently alien observations - SPS's - are put aside, all three rules correspond to the data fairly well: the percentage of wrong predictions is below 30% in all cases, well below

50% which we would expect if we were making purely random forecasts of the subjects' decisions.

The estimated versions of the rules turned out to correspond to the data about equally well or differently according to different measures so that it is hard to distinguish between them in terms of their relative strength of correspondence to the data. An exception to this ambiguity is perhaps estimation on the basis of low price runs only, where the Adaptation Rule seems to fit the data markedly better than the Improvement Rule.

As to the estimated values of parameters, all three rules treat the prediction π as useless: both γ and ϕ are estimated to be zero. The weight assigned by subjects to this supplementary piece of information may be rather sensitive to how the origin of it is described in the instructions for the experiment. It is quite possible that if we gave to π an interpretation different from the one we used (prediction by experts in the media), subjects might consider π more relevant and give it some weight.

The other estimates do not have this extreme character and most of them seem realistic. One could perhaps ask whether it is realistic that the rate of adaptation in the Adaptation Rule is about 1/4 for high price runs but between 1/2 and 2/3 for low price runs.

VI. Conclusion

The contribution of the present paper to the existing literature is twofold. First, three general search heuristics are formulated which seem a priori plausible as the basis for actual search behaviour. Each heuristic has its own logic and is general enough to be usable in various search settings differing in the degree of knowledge about the price distribution and/or in other aspects. In future research, of course, the heuristics can be further refined and enriched with other potentially relevant factors that we have not dealt with in this paper, such as a maximum number of search steps (in those cases where this number is limited), perceived increases of the general price level during the search, increasing urgency of the need for the good as search continues, increasing travel cost as additional shops are more and more distant, existence of more than one quote (brand) per shop (and therefore per one travel fee paid), non-zero probability that a previously spotted quote is no longer available, etc.

Second, three specific search rules are derived from these heuristics for the special case of a buyer searching for a low price in a little-known market. The parameters of these rules are estimated, using data from a small-scale experiment, and the goodness of fit is compared for the three rules.

The comparison of goodness of fit has not earmarked a clear winner among the three rules. How could this indeterminateness be cured? An obvious next step is to increase the number of observations. This may amplify differences in fit among the rules. Higher number of observation would also allow us to estimate the rules for various segments of the data. E.g., we could cluster the subjects according to which rule they seem most likely to use, or to group the subjects according to their characteristics such such age, shopping experience, sex, etc. (this might also allow us to predict what type of subject will use what rule). In addition, we might try different specifications for the rules. Finally, we could try various other particular ways of filling the three general heuristics with the information suggested as reasonable to be used.

A specific problem is the occurrence of SPS's. It is possible that an SPS is precisely what some actual buyers content themselves with instead of using any sophisticated rule, even when they have no idea about the price distribution. But if we assume that in real life this is an exception rather than rule, the experiment should induce subjects to avoid SPS's (except, of course, when an SPS is consistent with one of the rules). To eliminate thoughtless stopping at the first price seen, the amount to be gained by stopping at the first price should be decreased, e.g., by decreasing the show-up fee (which, however, means running the risk of fewer subjects turning up).

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