Do consumers not switch because they are not optimising?*

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Abstract

Search and switch costs are two market frictions that are well known in the literature for preventing people from switching to a new and cheaper provider. Previous experimental literature has studied these two frictions in isolation. However, field evidence show that these two frictions frequently occur together; recently a theoretical framework has been developed to study the interplay between these two costs (Wilson, 2012). This experiment tests if the individual behaviour under search and switch costs is in line with theoretical predictions derived from the optimal choice rule of Wilson. The results show that the crucial role of the search strategy: not only, according to Wilson model, the search cost has a greater deterrent impact on search than the switch costs, but also the sub-optimality of the search strategy is the major source of sub-optimality in the switching behaviour.

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1. Introduction

As an illustration of the kind of problem we investigate in this paper, consider a householder who uses gas for heating and cooking. Presently, the householder gets gas from a particular supplier, say British Gas. Daily she gets leaflets through the post, and messages on the web, pointing out that there are alternative suppliers[1]. The magazine *Which?* constantly urges people to think about switching to a new supplier. It appears that too few do, and that many households remain paying a price higher than they need to (e.g., Brennan, 2007; Giulietti et al., 2005). The reluctance to switch supplier has been shown to affect not only the energy market but also other important economic sectors such as health insurance and investment for retirement. Search and switching costs appear to be the main factors that deter consumers from switching to the best supplier.

In this study, we experimentally investigate the role of search and switching costs as determinants for non-switching and sub-optimal switching: one intention is to determine the relative importance of each cost in preventing switching in general; for this purpose we test the comparative static predictions of a standard model of search and switch (Wilson, 2012). On the other hand, we want to investigate to what extent the non-switching behaviour is optimal. To do so, we fit the Wilson model to the data. By using an experimental study, rather than field data, we can manipulate the costs of searching and switching, and hence measure the direction and strength of their effect on decision-making; to the best of our knowledge, none of the previous experimental studies analyzed search and switch costs together, altough these costs usually co-occur in the field. Also, the experimental setting allows us to isolate search and switching

[1] At the time of writing: Airtricity, Atlantic, Better Energy, Budget Energy, Co-operative Energy, Daligas, Ebico, Ecotricity, EDF Energy, Eon, Extra Energy, Firmus Energy, First Utility, Flow Energy, GB Energy, GnErgy, Good Energy, Green Energy UK, Green Star Energy, iSupply Energy, LoCO2, M & S Energy, Npower, OVO Energy, Power NI, Sainsbury's Energy, Scottish Hydro, Scottish Power, Southern Electric, Spark Energy, SSE, Swalec, Utilita, Utility Warehouse, Woodland Trust Energy, Zog Energy.

costs from other sources of non-switching that we can find in the field, and to compute the theoretical optimal choice to check if non-switching occurs optimally or not.

In Section 2 we briefly review the most relevant studies for our work; in Section 3 we present the theoretical framework for our experiment, the design of which is presented in Section 4. In Section 5 we present the results of the qualitative (5.1) and quantitative (5.2) predictions, and discuss the overall findings (5.3). We conclude in Section 6.

2. Related Literature and Research Questions

This paper belongs to a strand of literature that investigates the impact of search and switching frictions on the competitiveness of a market. In the recent past, policy makers have put considerable effort into increasing competition in various economic sectors such as telecommunications, energy, car, financial and health insurances. However, the existence of multiple suppliers has proved to be insufficient to achieve competitive outcomes: the reluctance of consumers to search and switch supplier implies sub-competitive outcomes (for example, Waterson, 2003). The relevance of this issue for policy-makers is indicated by the huge amount of effort spent on improving the search and switch behaviour of consumers. For example, the UK National Regulatory Authority of gas and electricity markets has created a page on their website to encourage consumers to switch to 'better' suppliers.

There has been a large volume of empirical studies aiming to quantify the costs that prevent consumers from switching, using survey data as well as structurally estimating demand. These frictions have been shown to significantly affect many economic activities such as online retail (Goettler & Clay, 2011), health insurance (Polyakova, 2016), telecommunication (Shcherbakov, 2016), energy provision (for example, Giulietti et al., 2005), retirement investment (Luco, 2019) and auto insurance (Honka, 2014).

It has emerged from these studies that, in order to derive policy-relevant recommendations, it is important, not only to quantify the overall switching costs, but also the different sources of these costs. For example, some of these studies have quantified different types of costs involved in the switching process – distinguishing proper switching costs from costs connected with search. Honka (2014) shows that search costs have a greater impact than switching costs in the US auto insurance market. However, Luco (2019) shows that the switching costs connected to the bureaucracy are more relevant than the cost of processing financial information in the Chilean retirement sector; the relevance of search and switching costs varies then according to the sector.

In the same spirit, our work aims to study the impact of difference frictions on switching behaviour. Our approach is, however, complementary to the empirical studies, since we do not need to estimate these costs (relying on identification assumptions), but we can manipulate their values. We can also define and implement them precisely: we implement them as monetary costs; a search cost is incurred once for every supplier searched; while a switch cost is incurred only if the consumer changes supplier. Everything else is maintained constant, so any other factors that may influence behaviour are excluded as sector specific effects.

There is some experimental literature on search and switch costs. While in practice, these two frictions usually occur together, experiments have typically studied them separately. There is a strand of experimental literature that examines how search costs affect individual and market behaviour. As to the effect on individual behaviour, there are studies (for example, Hey, 1981; Braunstein & Schotter, 1982; Kogut, 1990) which consider the impact of search cost on individual search behaviour and compare it with the predictions of search-theoretic models. Other studies consider the impact of search costs on the market: Davis & Holt (1996) show that, in an experimental post-offer market, prices are higher than the competitive prices when search costs are introduced. However, these prices are far from the monopolistic prices that the model of Diamond (1971) predicts in the presence of search costs. Similar results were found in the experiment of Abrams et al. (2000). A few experimental studies explore search cost in concentrated markets (for example, Moellers et al., 2016). Another stand of literature explores switching costs, that is, the cost of changing seller. This issue has been extensively studied theoretically (for a review see Farrell & Klemperer, 2007). The markets where there are switching costs are named "customer markets": all or some of the consumers are 'locked-in' with a seller due to switching costs. In general, firms have market power deriving from these switching costs, and they can exploit it by fixing higher prices. However, if the firms cannot discriminate between locked-in and new consumers, their market power is reduced. Cason & Friedman (2002) experimentally study a customer market with a post-offer mechanism and show that the prices fixed by the sellers are higher the greater is the proportion of attached consumers, and the lower is information on the other firms' prices. Morgan et al. (2006) study experimentally a customer market with both locked-in and informed consumers. They show that an increase of informed consumers leads to prices that are more competitive.

A recent theory paper by Wilson (2012) proposes a model with both search and switch costs. He shows that these two costs affect the equilibrium through different mechanisms, thus leading to predictions on the relative importance that each cost has on individual choices and market equilibrium: according to Wilson's analysis the search costs have a greater impact than switch costs on the market outcomes, and the differential importance of switching and search cost arises from the different ways in which these two cost affect the decision making. In our experiment, we have both these frictions, so we can assess their relative impact on search and switching behaviour. Schram & Sonnemans (2011) study search and switching costs in an experiment targeted to the study of health insurance policy. As in our experiment, search and switching costs are studied and manipulated together, but the search cost is manipulated changing the number of options, not varying the costs, and they do not have a theoretical model as a reference.

To the best of our knowledge, our experiment is the first that has both search and switching cost in an integrated setting, thus enabling us to distinguish the effect of the two costs on behaviour, and to compare actual behaviour with the theoretical predictions. We deliberately choose the simplest possible framework in order to focus on the key essentials. In the next paragraph we will describe the consumer's choice problem and present the optimal choice rule for the consumer derived from Wilson's model. Then, we will present the comparative static predictions from this optimal choice rule.

3. Theoretical Background

The consumer's decision problem can be described as follows. First, the consumer must decide whether to start searching for an alternative supplier; the decision on this will partly depend upon the cost of searching and partly on inertia connected with 'loyalty' to the present supplier. This latter can be represented by a 'cost of switching', which in our setting is monetary. Once started searching, the consumer must decide for how long search should continue; this will obviously depend upon the cost of searching (and the distribution of alternative offers). Having finished searching, the consumer should then decide which contract to enter into; this could be the existing one if the switch cost is too high. Under certain assumptions, an optimal search and switch strategy exists and can be calculated. To specify this, we borrow from Wilson (2012). He considers a market problem, in which there are firms/suppliers (reacting to consumer behaviour) and consumers (who are searching and switching). We shall borrow just the consumer side, taking the firms side as exogenous.

First, the optimal choice rule of the consumers is described. This is a version of the decision rule presented by Wilson (2012) modified in order to taking into account the features and the purpose of the present experimental analysis. Secondly, the comparative statics predictions that can be derived from this choice rule are stated.

3.1. The optimal choice rule

In the scenario considered by Wilson there are J firms with differentiated products. Each firm j's product has a consumer specific value, i.e. the consumer

i matching value is $\epsilon_{i,j}$. The consumers are locked-in with their local firm: they knows the value of the offer of the local firm, $\epsilon_{i,1}$, and its price, p_1, but they do not know the other firms' offers values and prices. She can search sequentially the offers and prices of the non-local firms. Since we will consider the supply side as exogenous, we fix prices equal to 0. For each search the consumer incurs a cost c. After she has searched as many firms as she wants or when she has searched all the market, she has to decide whether to buy from the local firm or from one of the searched offers from a non-local firm. In order to trade with a non-local firm she has to pay the switching cost s; there is no cost to trade with the local firm. The consumer earns the difference between the offer accepted and the price paid for that offer. The optimal strategy for searching and switching developed by Wilson is based on a reservation value, $\hat{x}$, that is computed as follows[2]:

$$c = \int_x^{\bar{\epsilon}} (\epsilon - x) g(\epsilon)\, d\epsilon$$

$\hat{x}$ is the value of the offer that would equalize the expected benefits from search to its cost. This is then the reservation value to be compared with the offers of the firms searched during the search process, and it can be shown that if the matching values are uniformely distributed, $g(\epsilon) = \frac{1}{\bar{\epsilon} - \underline{\epsilon}}$, the reservation value is

$$\hat{x} = \bar{\epsilon} - \sqrt{2c(\bar{\epsilon} - \underline{\epsilon})}$$

However, the switch cost has also to be considered at some stages of the choice process; the choice rule is composed of three steps:

[2]The formula reported in the text comes from this equality: $\epsilon = -c + \int_x^{\bar{\epsilon}} \epsilon' g(\epsilon') d\epsilon' + \int_{\underline{\epsilon}}^x \epsilon g(\epsilon') d\epsilon'$. That is, the reservation value x is the value that equalize the value of the current offer ϵ with the potential gains that the consumer would have finding an offer greater that the current one, weighted by its probability, $\int_x^{\bar{\epsilon}} \epsilon' g(\epsilon') d\epsilon'$, or lower than the current one,weighted by its probability, $\int_{\underline{\epsilon}}^x \epsilon g(\epsilon') d\epsilon'$, minus the cost of the search c

***STEP 1*: start search or accept local offer**

The consumer first has to choose if she accepts the local offer or she starts to search. In order to take this choice, she compares the "local reservation utility", $\hat{x} - s$, with the local firm's offer, $\epsilon_{i,1}$. She starts to search if[3]

$$\epsilon_{i,1} < \hat{x} - s$$

At this stage of the choice the consumer has to consider the fact that accepting the local offer implies that the switch cost s has not to be paid, instead any non-local offer discoverd during search would require the paying of the switch cost s in case of acceptance.

***STEP 2*: search among non-local firms**

If in *STEP 1* the consumer starts to search among non-local firms, she has then to decide when to stop. Since the switching cost will be paid for any non-local offer, the switching cost does not enter in the decision to search another non-local offer. The decision to search or stop at this stage is then based on the comparison between the non-local offer $\epsilon_{i,j}$ discovered and the general reservation value $\hat{x}$, and the switch cost s plays no role, and the choice is affected only by the search cost c and the drawn offer. The consumer stops searching when a non-local offer is such that:

$$\epsilon_{i,j} > \hat{x}$$

and she keeps searching otherwise.

***STEP 3*: choice among offers**

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[3] This formula follows from the equality $\epsilon - s = -c + \int_{x}^{\bar{\epsilon}} (\epsilon' - s) g(\epsilon') d\epsilon' + \int_{\underline{\epsilon}}^{x} (\epsilon - s) g(\epsilon') d\epsilon'$, that can be shown to be equal to $\hat{x} - s$.

Once the consumer decides to stop her search or she has searched all the market, she has to decide which option is to be accepted. At this stage the switch cost comes into play again, as the comparison between the non-local offers and the local offer has to take into consideration the payment of cost s when accepting a non local offer. The consumer i accepts the option that maximise her reward:

$$b = max\{\epsilon_{i,1}, \epsilon_{i,j} - s\}$$

The search cost, $c * number\ of\ searches$, has to paid both if a local or non-local offer is accepted.

Wilson (2012) provides an analytical derivation of this optimal decision rule, and we refer to his work for further details on its derivation. As already pointed out, the optimal choice rule presented in this chapter is a simplified version of that of Wilson's. Indeed, as in the present work we aim to investigate the optimality of consumer behaviour, the supply side is exogenous. Hence, we set the prices to a fixed level equal to zero; it follows that the expected difference in prices has not to be considered during the search process, and prices do not enter in the final step of the reward computation. Also, the choice rule presented by Wilson is modified in not allowing for the outside option of not buying, as in the experiment negative values are not possible, and choosing the outside option would be then not optimal or just indifferent compared to any of the possible rewards.

3.2. Comparative Statics Predictions

According to the choice rule described, we can derive comparative statics hypotheses on how behaviour should change when the values of the search and switching costs, c and s, change.

1 **A rise in search costs c decreases the likelihood that a consumer starts to search beyond her local firm, and it increases the likelihood of acceptance of low local offers.**

A higher value of c decreases the reservation utility $\hat{x}$. It follows that in *STEP 1* the local reservation utility is lower, and then it is more likely that the consumer accepts the local offer and does not start to search. Also, as $\hat{x}$ is lower the minimum acceptable offer decreases.

2 **A rise in switching costs s decreases the likelihood that a consumer starts to search beyond her local firm, and increases the likelihood of acceptance of low local offers.**
A higher value of s decreases the local reservation utility $\hat{x} - s$, and then it is more likely that the consumer accepts the local offer and does not start to search in *STEP 1*, and this decreases the minimum acceptable local offer.

3 **An increase in search cost c has a stronger impact on the choice of starting search than an increase in the switch cost s.**
In the computation of the net benefit of start searching the consumer puts a greater weight on the search cost c than on the switch cost s, since the probability of paying the search cost is equal to one, instead the probability of paying the switch cost s is lower than one and equal to the probability of finding a better offer[4].

4 **A rise in cost c reduces the number of non-local searches and decrease the minimum offer necessary to stop search, given that the consumer started to search.**

As in *STEP 2* the reservation utility $\hat{x}$ which is compared with any non-

[4]The formula reported in footnote 3 shows this point.

local offer is lower, it follows that the acceptance of any non-local offer is more likely and the number of searches needed to find an acceptable offer tends to decrease as well as the number of points accepted.

5 **A rise in cost s does not affect the number of non-local searches and the minimum offer necessary to stop search, given that the consumer started to search.**

Unlike cost c, in *STEP 2* the switching cost s is not considered as it would not affect any non-local offer. Hence, it does not affect the number of non-local searches once the search has started.

6 **If the consumer stops searching before the entire market has been searched, the last searched non-local offer is accepted.**

If the consumer i stops searching, she must have found an offer $\epsilon_{i,j} > \hat{x}$. This last searched local offer must then dominate the local offer since the condition to start search is that $\epsilon_{i,1}+s < \hat{x}$. Also, this last offer dominates the previous non local-offers since they must be lower than $\hat{x}$, otherwise the search should have been already stopped.

7 **If all the market has been searched, a rise in s reduces the likelihood that a consumer switches to a non-local firm; instead, a rise in c does not affect the final choice.**

If the consumer searches all the market, it means that she has not found an option that exceedes the reservation utility threshold earlier. She has to consider which is the best option among all previous ones, hence also the local one. This prediction comes from *STEP 3* of the choice rule: once the consumer stops searching, she chooses the best deal which implies comparing local and non-local offers discounting the cost s from non-local ones. Notice that the cost s becomes relevant only if all market has been searched: if the search stops before, this means that a non-local option that clearly dominates the local one has been found.

The cost c will paid whatever is the final choice, a local one or a non-local one, hence it will not affect this final comparison.

4. Experimental Design

We implemented two treatments, which differed in the number of firms in the market. Our first and *main* experiment involved 124 subjects, and it was run in February 2019. We then implemented an *extension* with 39 subjects to test the robustness of our results to the number of firms in the market in July 2019. The *main* study had 5 firms, the *extension* 10[5].

Subjects were mainly students at the University of York, recruited with the *hroot* software. The experiment was an individual one, as it was designed to test just the consumer side of the Wilson model. Subjects were given printed instructions, which were read out to them over the tannoy system by an experimenter. They were given the opportunity to ask questions. Then they turned to the experiment, programmed in Z-Tree Fischbacher (2007). In the instruction the participants were given an example; they answered control questions on the screen and played one trial round before they started on the real problems. The instruction are in Appendix A and the software, including the control question, is available in the supplementary material.

There were 80 problems in total, chosen to give a rich quantity and quality of data. They key parameters of interest were c, the search cost and s, the switch cost. In the main experiment, we had four values of each (c: 0, 0.25, 0.5 and 1; s: 0, 1, 2 and 4) and we implemented all 16 combinations of these (giving the total of 80 problems), each repeated 5 times, and presented in a random order. In each problem subjects were informed of the values of c and s, as well as the offer from the local firm. All offers were randomly generated from a uniform distribution over the interval from 8 to 22. They were then asked if they wanted

[5] We ran a pilot to test the software in December 2018 with 5 subjects. The subjects that participated in the pilot experiment were not invited to the *main* and *extension* experiments. Also, those who participated in the *main* experiment were not invited to the *extension* experiment.

to buy from the local firm, or to search the offer from another firm. If they chose the former then that would be the end of that problem and their points earned would simply be the offer from the local firm.

If they chose to search, they could do so as often as they wanted, up to the number of firms in the market. When they decided to stop searching they were asked from which firm they wanted to buy. If it was the local firm, their points earned would be the offer from the local *minus* the total amount that they had spent on searching (the search cost times the number of firms that they had searched). If it was one of the non-local firms, their points earned would be the offer from the non-local firm chosen *minus* the total amount that they had spent on searching and *minus* the switch cost.

In the *extension* experiment, as we wanted to keep the setup of the experiment as close as possible to the *main* experiment, we kept the range of the offer between 8 and 22, and we have a similar but not identical set of c and s parameter values,(c: 0, 0.125, 0.25 and 0.5; s: 0, 0.5, 1 and 2). Indeed, we did not include the extremely high values of the search and switching cost parameters (i.e., $c = 1$ and $s = 4$) because it would have implied the possibility of negatives outcomes. In this setup the subjects are presented with the same number of different combinations of the parameters and the same number of repetitions of each combination both in the *main* experiment and in the*extension* experiment.

The participants were paid on the basis of the points earned on a randomly chosen one of these problems. In addition, they received a £2.50 show-up fee. Points earned were converted into pounds by multiplying them by 0.65.

An addition feature of the design is that the *main* experiment contains a between-subjects treatment, the *Display Cost* treatment: half of the subjects were shown on the screen how much they have spent so far in the search[6]. The purpose of this between-subject treatment is to test how presenting information on search costs affects the decision-making. To preemt the results on this latter

[6]The screenshots of the cost display can be found in the Instructions in Appendix A.

issue, it seems that an account of the accumulated search costs increses the deviations from optimality as it suggests to not search at the margin.

Following the 80 problems, subjects were asked to complete a short demographic questionnaire. The average payment to subjects was £13.50 in the *main* experiment, and £14.50 in the *extension* experiment, including the show-up fee. The subjects spent on average 2 hours in the laboratory, including reading the instruction and the payment.

5. Results

In this section we will first presents the results of the comparative static testing (5.1): it will be shown how much the participants' behaviour is in line with the qualitative predictions of the theory, in particular, the direction and strength of the effect of the search and switch cost on the search and switch behaviour. Second, the testing of the quantitative predictions of the theory will be presented (5.2), considering both a deterministic(5.2.1) and a stochastic implementation of the model (5.2.2). In 5.3 we discuss the results.

5.1. Comparative statics testing

In this section we report the results of the comparative static hypotheses that aim to test whether the individual behaviour in the experiment is consistent with the qualitative predictions from the optimal choice rule. We will first present the analysis of the *main experiment*, with 5 firms, and then the results of the *extension experiment*, with 10 firms, in a separate paragraph.

In the first row of Table 1 we have the proportion of choices where the participants started to search at each level of the search costs; we can see that this proportion decreases as search cost increases; we observe the same decreasing pattern also when the switching cost increases; regression (1) in Table 2 shows that the negative effect of c and s on the probability of starting the search is also strongly statistically significant. Further, according to the marginal effects reported in the second column of the same table, the effect of the search costs c is greater than the effect of s: an increase of c decreases on average the probability of starting search by 27 percentage points, while an increase of s decreases on average the probability of starting search only by 5 percentage points. Regression (2) in Table 2 further supports these previous conclusions: among those that do not start to search, the average number of points accepted is lower as the search and switching costs increases, and this is in line with the theory that predicts a lower reservation utility as c and s increase, and hence the willingness to accept lower offers implies that people start to search less frequently. Also, the marginal effect on the number of points accepted as initial offer is greater for c than for s: on average an increase of c decreases the initial offer accepted by 0.90 points, while s decreases it by 0.30 points[7]. The direction and strength of the effect of c and s on the initial choice of starting to search are then in line with the comparative static hypotheses 1, 2 and 3.

Table 1: Descriptive Statistics of Search and Switch Costs's effect - *Main* Experiment

This table displays the mean values of *Start Search*, *Initial Accepted Points* and *Number of Searches* for each search and switching cost level.
Start Search is a dummy variable equal to 1 when subjects start to search among non-local firms.
Initial Accepted Points is the number of points accepted as initial offer without searching.
Number of Searches is a discrete variable that assumes integer values from 0 to 4.
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Search Cost	$c = 0$	$c = 0.25$	$c = 0.5$	$c = 1$
Start Search	0.88	0.64	0.59	0.55
Initial Accepted Points	18.96	18.61	18.27	17.76
Number of Searches	3.23	1.55	1.31	1.07
Switch Cost	$s = 0$	$s = 1$	$s = 2$	$s = 4$
Start Search	0.77	0.70	0.64	0.55
Initial Accepted Points	19.05	18.52	18.41	17.55
Number of Searches	2.18	1.80	1.68	1.49

[7] Unlike the percentage points, here 'points' is referred to the experimental currency unit that defines the offers to the subjects during the experiment.

Table 2: Comparative Statics 1, 2 and 3 - *Main* Experiment

This table displays the two regressions. Regression (1) is mixed-effect probit regression where the dependent variable is *Start Search*, a dummy variable equal to 1 if they start search, 0 otherwise. It is reported the average marginal effect in the second column. Regression (2) is a mixed-effect regression where are considered only the observations where there is not search; the dependent variable, *Initial Offer Accepted*, the number of points of the initial offer - that is the one accepted when there is not search.
All these regressions control for demographic variables and *Period* and *Session* number, and have random intercept and random slopes for c and s. Table B.13 in the appendix reports the full regression with controls.
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	(1) *Start Search*	*Marg. eff.*	(2) *Initial Offer Accepted*
c	-1.76***	-0.27	-0.91***
	(0.11)		(0.23)
s	-0.32***	-0.05	-0.30***
	(0.03)		(0.06)
Observations	9920		3323

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Once a consumer starts to search, the theory predicts that the number of non-local searches should be lower as c increases, and should not depend on s. Regression (1) in Table 3 confirms the significant negative effect of the search costs on the number of non-local searches; this confirms comparative static hypothesis 4. Unlike the prediction of comparative static 5, the switching costs has a significant negative effect on the number of non-local searches, although the size of this effect is very small; thus, comparative static hypothesis 5 is not confirmed. However, the effect of the switching cost becomes insignificant if we exclude choices that are inconsistent, as shown in Regression (2) of Table 3. Indeed, unlike as predicted by comparative static hypothesis 6, around 11% of the observations are dynamically inconsistent: the subjects choose a previously unchosen option before having searched all the market: to have an idea of the size of the phenomenon, 90% of the subjects do at least one inconsistent choice, and just 15% of the subjects do more than the 25% of thier choices inconsistently. Note that if we consider only the inconsistent choices (1170 observations, i.e. the 11.8% of choices), the switching cost has a marginally significant negative effect on the number of non-local searches (this regression is reported in Table B.15 in the Appendix). This suggests that the lack of significance of the switching costs in regression (2) of Table 3 does not depends on the lower number of observations with respect to regression (1) of the same Table, but instead on the presence of the inconsistent observations. This type of inconsistent behaviour has been observed in previous experimental tests of search models, and it has been explained in terms of sunk costs (e.g., Kogut, 1990): subjects do not search at the margin, they instead consider the change in their wealth deriving from a further search, that is, they fail to consider the past search costs as sunk costs. Our intuition of why the inconsistent choices are those where the switching cost s have an effect (that should not have) on non-local search is that subjects behaving inconsistently fail to consider the switching cost as a sunk cost (as it is in the non-local search), consistently with what has been shown for the search costs in previous studies.

Finally, the hypothesis in comparative static 7 is confirmed with respect to the switching costs: if all the market has been searched a rise in the switching cost s increases the likelihood of accepting the initial offer. However, also a rise in the search cost c increases the likelihood of accepting the initial offer - which is not consistent with the theory: once all the market has been searched the search costs will have to be paid whatever is the final option chosen. This again can be explained by the sunk cost fallacy, i.e. an evaluation that is not at the margin, but instead considers the effect of search and switching costs on overall gains: having spend an higher amount of money on search may lead to accept the initial offer to not pay the switch cost that would further reduce the final gain.

Extension. Table 4 shows that in the *extension* experiment there is the same tendency that we found in the *main* experiment with respect to the relation between search and switching costs and the decision of starting to search: both the

Table 3: Comparative Static 4, 5 and 7 - *Main* Experiment

Regression (1) is a tobit regression upper-censored at 4 where the number of non-local searches is the dependent variable. It is reported the *Marginal Effect* on the expected value of the censored outcome.
Regression (2) is the same as regression (1), but it considers only consistent choices.
Regression (3) is a mixed-effect probit regression that considers the case where all the market has been searched, and *Initial* is equal to 1 if the initial (local) offer is accepted, 0 otherwise.
All these regressions control for demographic variables and *Period* and *Session* number; they have random intercept; also, regressions (1) and (2) have random slope for c. Table B.14 in the appendix reports the full regressions with controls.
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	(1) *n of Non-Local Searches*	*Marg. eff.*	(2) *n of Non-Local Searches (consistent choices only)*	(3) *Initial*
c	-2.739***	-1.59	-3.066***	0.891***
	(0.112)		(0.126)	(0.231)
s	-0.0598***	-0.03	-0.0116	0.520***
	(0.0220)		(0.0297)	(0.0370)
Observations	6597		5427	2712

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

search and switching costs have a deterrent impact on starting search, and the number of points accepted as initial offers tend to decrease as c and s increase. Table 5 confirms that the negative effect of the search cost and switching costs on starting search is significantly negative, and that this effect is greater for the search cost than for the switching cost. Hence, comparative statics 1,2 and 3 are confirmed[8]

Table 6 confirms comparative statics 4 and 5: the number of non-local searches are negatively affected by the level of search costs, but not by the level of switching costs.[9] As in the *main* experiment, we find that comparative

[8]Unlike the *main* experiment, the number of points accepted as initial offer are not significantly affect by the level of search (p-value= 0.18 in the regression) and switch costs (p-value=0.37), altough the tendency shown in Table 4 is consistent with the hypothesis. The lack of statistical significante might depend on the lower number of subjects.

[9]However, notice that the fact that comparative static 5 is confirmed here unlike the *main* experiment, it may depend on the lower number of subjects. Indeed, in the *main* experiment

Table 4: Descriptive Statistics of Search and Switch Costs's effect - *Extension* experiment -

This table displays the mean values of *Start Search*, *Initial Accepted Points* and *Number of Searches* for each search and switching cost level.
Start Search is a dummy variable equal to 1 when subjects start to search among non-local firms.
Initial Accepted Points is the number of points accepeted as initial offer without searching.
Number of Searches is a discrete variable that assumes integer values from 0 to 9.
.

Search Cost	$c = 0$	$c = 0.125$	$c = 0.25$	$c = 0.5$
Start Search	0.92	0.75	0.71	0.65
Initial Accepted Points	20.11	19.56	19.01	18.95
Number of Searches	7.50	2.76	2.42	2.02
Switch Cost	$s = 0$	$s = 0.5$	$s = 1$	$s = 2$
Start Search	0.81	0.76	0.77	0.67
Initial Accepted Points	19.80	19.11	19.21	18.94
Number of Searches	4.13	3.74	3.55	3.29

Table 5: Comparative Statics 1, 2 and 3 - *Extension* Experiment

This table displays the two regressions. Regression (1) is mixed-effect probit regression where the dependent variable is *Start Search*, a dummy variable equal to 1 if they start search. It is reported the average marginal effect.
Regression (2) is a mixed-effect regression where are considered only the observations where there is not search; the dependent variable, *Initial Offer Accepted*, the number of points of the initial offer- that is the one accepted where there is not search.
All these regressions control for demographic variables and *Period* and *Session* number, and have random intercept and random slopes for c and s. Table B.16 in the appendix reports the full regression with controls.
.

	(1)		(2)
	Start Search	*Marg. eff.*	*Initial Offer Accepted*
c	-3.28***	-0.47	-1.04
	(0.40)		(0.78)
s	-0.46***	-0.06	-0.18
	(0.08)		(0.20)
Observations	3120		761

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Comparative Statics 4, 5 and 7 - *Extension* Experiment

Regression (1) is tobit regression upper-censored at 9 where the number of non-local searches is the dependent variable. It is reported the *Marginal Effect* on the expected value of the censored outcome.
Regression (2) is the same as regression (1), but it considers only consistent choices.
Regression (3) is a mixed-effect probit regression that considers the case where all the market has been searched, and *Initial* is equal to 1 if the initial (local) offer is accepted, 0 otherwise.
All these regressions control for demographic variables and *Period* and *Session* number; they have random intercept and (1) and (2) and have random slope for c. Table B.17 in the appendix reports the full regression with controls.
.

	(1) *n of Non-Local Searches*	*Marg. eff.*	(2) *n of Non-Local Searches (consistent choices only)*	(3) *Initial*
c	-13.43***	-8.74	-15.22***	2.99**
	(0.82)		(0.91)	(1.42)
s	-0.26	-0.17	-0.21	0.54***
	(0.16)		(0.20)	(0.16)
Observations	2359		1945	716

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

statics 6 and 7 are not confirmed: 13.25% of choices are not consistent (and 90% of the subjects show at least one inconsistent choice, but the majority of the subjects show inconsistency in less than 10% of the choices), and once all the market has been searched the search costs matters for the final choice. As we previously discussed, these deviations can be explained by the sunk cost fallacy.

5.2. Quantitative predictions' testing

We now analyze how close behaviour in the experiment is with the quantitative predictions from Wilson's model. In 5.2.1 we consider the predictions from a deterministic implementation of the model, and in 5.2.2 we consider a stochastic implementation of the model.

the effect of s on non-local search was very small and an effect of the same size might not be detected with less subjects.

5.2.1. Deterministic Wilson's Model

From the deterministic model we can derive precise predictions on the optimal final choice and strategy in terms of number of searches and switching behaviour. We will first present the analysis of the *main* experiment, with 5 firms, and then the results of the *extension* experiment, with 10 firms, in a separate paragraph: a summary of the results in the *main* experiment are reported in Table 9, and in the *extension* experiment in Table 12.

Around 81% of the actual choices are equal to the final optimal choices predicted by the model. However, this does not necessarily imply that the search and switch strategy to get to that final choice is optimal as well: people could not search optimally even if they end up choosing the optimal option. We observe that the decision to start or not start searching is optimal in 86% of the choices: we should observe that people start a non-local search in 70% of the choices observed, instead they started to search just in 66% of choices; indeed, in 9% of choices they did not start to search even if it was optimal [10], and in 5% of choices subjects actually started to search even if it was not optimal [11]. The most frequent type of deviation is then not starting search when it would be optimal.

Also, Table 7 and Table 8 show that the number of searches is lower than optimal: the mean deviation from the optimal number of searches (optimal number of searches - actual number of searches) is positive, 0.33, and strongly significant[12], and the actual number of searches is optimal only in 66% of the choices; indeed, in 26% of choices show there are less searches than optimal [13], and in

[10] 94% percent of subjects show this behaviour in at least one choice, and 9% of the subjects do it in more than 10% of their choices.

[11] 77% of subjects start search even if they should not at least in one choice, and 15% of the subjects do it in more than 10% of their choices.

[12] The significance of this deviation comes from a mixed effect regression with random intercept not reported in the paper; the dependent variable is the deviation and there are no independent variables. The significance level is that of the intercept.

[13] All subjects do at least a choice where they search less than optimally, 91% of the subjects do it in more than 10% of their choices, 60% of the subjects do it in more than 20% of their

8% of the choices they search more than what would be optimal[14]. Even if we consider only those choices where a subject starts optimally a non-local search we again find a positive and significant average deviation from optimal search equal to 0.23[15].

We can preliminarily conclude that the there is the tendency to search less than optimally and sometimes the subjects do not even start search when it would be optimal. This inertia cannot be explained by search and switching costs because the optimal predictions of the model already account for these costs.

Let us now analyse the optimality of switching behaviour, and how this is related to search behaviour. According to the theoretical predictions, we should observe a switch to a non-local option in 60% of choices, but we actually observe switches only in 53% of choices. Overall, the 89% of the choices are optimal, i.e. subjects accept the initial offer when it is optimal and accept an offer that is not the initial one when it is optimal to switch[16]. Indeed, there are 11% of the actual switch choices that are not optimal: in 9% of choice subjects do not switch even if it would be optimal, and in 2% of choices subjects switch even it is not optimal. In addition, among those who switch when it is optimal to switch, not all end up switching to the optimal offer: in 13% of the choices where we observe a switch when it is optimal not to accept the initial offer, there is a switch to an option that is not the optimal final choice, meaning that even if it would be theoretically optimal to choose an option that is not local and the subject actually switch, they switch to an option that is not the theoretically optimal choice. These non-optimal switching behaviours are strictly connected to non-optimal search: if the subjects do not search enough to find the the-

choices, and 10% of the subhects do it in more than 50% of their choices.

[14] 88% of subjects do at least a choice where they searched more than optimally, 30% of the subjects do it in more than 10% of their choices, and 8% of the subjects do it in more than 20% of their choices.

[15] 20% of the choices show less searches than optimal and all subjects shows this behaviour at least in one choice

[16] Note that this percentage does not consider the fact that subjects could switch to a non-local offer that is not the optimal one. We will consider this type of sub-optimality later in this paragraph.

oretical optimal choice, they could find not convenient to switch or switch to an option that is not the theoretically best choice. Indeed, if we restrict our observations to those where the subjects search optimally, in 98% of the choices subjects chose the optimal option, and in 99% of the choices they show an optimal switching behavior. Also, if we consider the choices where the search is not optimal, in 96% of the choices subjects succeed in choosing the conditionally best option[17].

Table 7: Mean Number of Searches - *Main* Experiment

This table displays the mean values of *Number of Searches*,

	$c=0$	$c=0.25$	$c=0.5$	$c=1$	*Total*
$s=0$	3.59	2.08	1.73	1.31	2.18
$s=1$	3.27	1.53	1.29	1.13	1.81
$s=2$	3.12	1.37	1.22	1.03	1.69
$s=4$	2.94	1.20	1.01	0.79	1.49
Total	3.23	1.55	1.31	1.07	-

Table 8: Mean Deviation from Optimal Number of Searches - *Main* Experiment

This table displays the mean values of *Deviation of Searches=Optimal N of Searches-Actual N of Searches*,

	$c=0$	$c=0.25$	$c=0.5$	$c=1$	*Total*
$s=0$	0.41	0.44	0.24	0.1	0.30
$s=1$	0.50	0.70	0.60	0.23	0.51
$s=2$	0.27	0.61	0.41	0.17	0.36
$s=4$	0.05	0.38	0.17	0.1	0.17
Total	0.31	0.53	0.36	0.15	-

Extension. We now present how the data of the extension experiment fit the predictions of the deterministic Wilson models.

75% of the final choices are equal to the optimal one. This again do not mean that also the search and switch strategy is optimal even if the final choice is the same that the model predict; in general, it would be optimal to start search

[17]That is, they choose the best option in the searched set of options.

Table 9: Optimality of behavior - *Main* Experiment

This table reports the percentage of choices where respectively the subjects chose the optimal final offer (*Optimal Choice*), started to search optimally (*Optimal Start Search*), searched optimally (*Optimal Search*), chose the local offer when it was optimal (*Optimal Switch*), and chose the optimal final offer conditionally to the actual number of search when they didn't search optimally (*Coditionally Optimal Choice*).

Optimal Choice	*Optimal Start Search*	*Optimal Search*	*Optimal Switch*	*Conditionally Optimal Choice*
81%	86%	66%	89%	96%

in 80% of the choices, but we observe that subjects start search in 75% of the choices; in 89% of the choices subjects start search according to the model predictions: the difference between the actual and the optimal starts of the search are given by a 8% of the choices where subjects should start search and instead they do not start, and 3% of the choices where they start search even if it is not optimal.

More generally, the search behavior is optimal only in 63% of the choices: in 29% of the choices they search less than it would be optimal, and in 8% if the choice more than optimally; indeed, the deviations of from the optimal number of searches is positive, 1.12, and significantly different from zero. As in the *main* experiment , we conclude that there is a tendency to search less than optimally.

The switching behavior is now considered: it would be optimal to switch in 76% of the choices, but actually we observe switch in 68% of the choice; the percetage of choices where the switching behaviour is equal to the one predicted in the model is 89% : in 9% of the choices there is not switch when there should be, and in 2% of the choices there is switch when there should not be.

We further consider when there is a switch if this lead to choose the optimal offer: in 84% of the choices where the switching behavior is optimal, the optimal final offer is chosen. Again, the sub-optimality in switch behavior and in the final offer chosen is strictly connected to sub- optimality in search: when the search behavior is optimal, 99% of the choices are optimal in terms of switch and 98% of the choices are optimal in terms of final offer; also, note that when the search is not optimal, in 97% of the choices the choice is the conditionally optimal one. Hence, the main source of sub-optimality is then the search behavior: subjects do not search enough to find the optimal choice. Table 12 summarizes the main findings on the optimality of behavior in the *extension* experiment .

Table 10: Mean Number of Searches - *Extension* Experiment

This table displays the mean values of *Number of Searches*,

	$c = 0$	$c = 0.125$	$c = 0.25$	$c = 0.5$	*Total*
$s = 0$	8.26	3.36	2.49	2.40	4.13
$s = 0.5$	7.84	2.63	2.53	1.96	3.74
$s = 1$	7.2	2.69	2.47	1.84	3.55
$s = 2$	6.71	2.38	2.20	1.86	3.29
Total	7.50	2.76	2.42	2.02	-

Table 11: Mean Deviation from Optimal Number of Searches - *Extension* Experiment

This table displays the mean values of *Deviation of Searches=Optimal N of Searches-Actual N of Searches*,

	$c = 0$	$c = 0.125$	$c = 0.25$	$c = 0.5$	*Total*
$s = 0$	0.73	1.23	0.99	0.19	0.79
$s = 0.5$	1.16	1.77	1.10	0.43	1.11
$s = 1$	1.80	1.99	1.33	0.26	1.35
$s = 2$	2.29	1.35	0.90	0.37	1.23
Total	1.50	1.59	1.08	0.31	-

Table 12: Optimality of behavior with 10 offers

This table reports the percentage of choices where respectively the subjects chose the optimal final offer (*Optimal Choice*), started to search optimally (*Optimal Start Search*), searched optimally (*Optimal Search*), chose the local offer when it was optimal (*Optimal Switch*), and chose the optimal final offer conditionally to the actual number of search when they didn't search optimally (*Conditionally Optimal Choice*).

Optimal Choice	*Optimal Start Search*	*Optimal Search*	*Optimal Switch*	*Conditionally Optimal Choice*
75%	89%	63%	89%	97%

We can summarise the results of this section saying that the actual behaviour does not fit perfectly the quantitative predictions of the deterministic version of Wilson's model; this is not surprising as there is no theory able to explain perfectly actual behaviour of the subjects as there is always some randomness in human behaviour; for this reasons, in the next section we specify and estimate a stochastic version of Wilson's model to account for this randomness, and see if the estimated parameters are sensible. Also, although the deviations from the deterministic predictions go in both directions (people sometimes search too little and sometimes too much), there is a prevalence of deviations toward searching less than optimally, and this suggest a systematic tendency to do so rather than a random error in behaviour. Risk-aversion can explain why the number of searches is systematically lower than predicted by the Wilson's model that assumes risk neutrality. Hence, in the stochastic implementation of Wilson's model that we will present later we will introduce risk-aversion, and we will show that taking risk attitudes into account significantly improves the explanation of the data.

5.2.2. Stochastic Wilson's Model

We now turn to fitting the stochastic Wilson model to the data. We do this subject by subject. In order to do this, we need to impose some stochastic structure. We build this stochastic story on top of the normalised[18] *optimal* reservation value $\hat{X} = \frac{\hat{x}-\underline{\epsilon}}{\bar{\epsilon}-\underline{\epsilon}}$. This must lie between 0 and 1. We adopt the most obvious stochastic specification: that the normalised *actual* reservation value, X, has a beta distribution centred on the normalised optimal reservation value; that is that:

$$X \sim Beta(\alpha, \beta)$$

where $\alpha = \hat{X}(p-1)$ and $\beta = (1-\hat{X})(p-1)$, so that $E(X) = \hat{X}$ and $Var(X) = \frac{\hat{X}(1-\hat{X})}{p}$.

[18]The range of offers is $[\bar{\epsilon}, \underline{\epsilon}]$. We denote normalised values with UPPER CASE and unnormalised with lower case.

Here, the parameter p denotes the *precision* of the process: the higher it is, the more precise is the subject.

Note that, under this stochastic specification, if $\hat{X} = 0$ then $\alpha = 0$ and so subjects should put $X = 0$, and therefore subjects should always search all the market. This is a special case, and in our experiment occurs when when $c = 0$. Another theoretically possible special case is when $\hat{X} = 1$ then $\beta = 0$ and so subjects should put $X = 1$, and therefore subjects should never start search, and instead accept the initial offer. However, subjects could actually start/continue search when they should not, and do not start/continue search when they should. To account for this we include a *tremble*, t. We also include the tremble when, after stopping searching, subjects do not accept the best offer (net of any switching cost) that they have found.

Therefore, for a risk-neutral subject, there are two parameters to estimate: the precision p and the tremble t. For the first data set (124 subjects in February 2019) the mean estimated precision was 14.59 and the average estimated tremble was 0.066. For the second data set (39 subjects in July 2019) the corresponding figures were 18.24 and 0.042.

In a rather trivial sense, the Wilson model fits the data as the estimated precision and the tremble parameters are sensible. It also can be shown to fit the data better than a model that says that the subjects were choosing randomly. However, this not a very stringent null to test the theory against. A better null is assuming that subjects have a fixed reservation value, which does not depend on the key parameters c and s. Fitting this requires estimating the precision, the tremble and the (fixed) reservation value. For the first data set, the mean estimated precision was 8.00, the mean estimated tremble was 0.060, and the mean estimated fixed reservation value was 0.737. For the second data set (39 subjects in July 2019) the corresponding figures were 8.41, 0.028 and 0.84. More importantly, this arbitrary reservation value story actually fitted the data worse (as measured by the log-likelihood) than the Wilson story for 114 of the 124 subjects in the first data set and for 33 of the 39 subjects in the second data set. Hence, having a reservation value that depends on the search and switching costs is a valuable features of the Wilson model in order to explain the data.

At this point we should remind the reader that the 'Wilson model' that we are testing assumes risk-neutrality. This seems a very dubious assumption for the typical subject pool. Fortunately, we can extend this basic model to a risk-averse DM – as long as we assume that the DM has Constant Absolute Risk Averse (CARA) preferences – in which case the reservation value is independent of past searches. We can show (see the Appendix) that the reservation value is the solution to the following equation:

$$\hat{x} = (\overline{\epsilon} - \underline{\epsilon})e^{-rc} - \frac{1}{r} + \frac{e^{-r\overline{\epsilon}}e^{r\hat{x}}}{r}$$

where r is the coefficient of absolute risk aversion.

We have fitted this model to the data. Using a likelihood ratio test, we can show that for 57 (52) out of the 124 subjects in the *main* experiment, the risk-averse model fitted the data significantly at 5% (at 1%) better than the risk-neutral model. For the *extension* experiment, the corresponding figures were 18 (17) at 5% (1%) [19].

[19] In the main experiment the risk aversion is 0.33, the precision parameter is 16.98, and the tremble parameter is 0.08; in the extension experiment the risk aversion is 0.69, the precision parameter is 7.10, and the tremble parameter is 0.05

5.3. Discussion

According to the comparative static analysis, the theoretical model provided by Wilson (2012) predicts correctly the direction and relative strength of the search and switch costs on search behaviour: these costs have a deterrent effect on the number of searches and the effect of search costs is considerably stronger than the switch costs, and this finding is robust to the number of firms. We also find some deviations from the qualitative predictions that we can derive from the model: subjects show an inconsistent behaviour in a small, but significant proportion of choices. This is a well-known fact in experiments on search that can be explained by the sunk cost fallacy (e.g., Kogut, 1990). Although this type of the deviation is not crucial for our testing, as we are primarily concerned with the effect of introducing switch costs in the standard search framework, it is interesting to note that the sunk cost fallacy could explain other qualitative deviations that we observed; in particular, the significant effect of the switching costs in the non-local search and the effect of the search cost on the final decision of accepting the local offer once all the market has been searched can be explained by the fact that the switching costs and the search cost are not considered as sunk costs. Also, in our experiment we see that the percentage of choices that show inconsistency increases when the subjects are in the *Display Cost* treatment, that is when the search cost accumulated until that point of the search are shown on the screen (see Table B.18 in Appendix A); this cost display seems to had the effect of suggesting to the subjects to take into account the past search costs, and push them toward the sunk cost fallacy and then inconsistency.

Turning to the optimality of behavior compared to the quantitative predictions of the model, the subjects shows an inertia that cannot be explained by search and switching costs: they tend to search less than optimally, and sometimes do not even start search when it would be optimal. Also, the sub-optimality in search behaviour drives other sub-optimal behavior as not choosing the best option and not switching optimally. Hence, our results shows that the search strategy has a crucial role in preventing the achievement of a competitive market outcome, not only because, in line with the model predictions the search costs have a greater deterrent effect than switching costs in searching the offers on the market, but also because the source of sub-optimality behaviors are the in search strategy. Previous theoretical and experimental literature suggest that the tendency of searching less than optimally can be explained by risk-aversion (e.g. Braunstein & Schotter, 1982); also, it is a well-know fact that human behavior is charaterized by some randomness - despite the goodness of the model taken into account. Thus, in 5.2.2 we implemented a stochastic version of the Wilson model and checked if the parameters capturing randomness are sensible and if the risk-aversion matters for explaining the data. Our fitting of the stochastic model shows that the Wilson model captures some important feature of subjects' behavior; indeed, not only does the model fit the data better than a random choice model, but also better than a model with fixed reservation utility. Hence, the relation between c and s and the reservation utility in the model captures an important feature of the decision making. Also, the parameters connected to randomness of behavior (p and t) are sensitive, and introducing risk-aversion improves the fit with the data. We can then conclude that future attempts to develop and test models of search and switching behavior should consider the Wilson model a sensitive framework for this purpose, and taking into account that risk-attitudes add explanatory power to the model. Altough the deviations that we found in terms of inconsistency and other qualitative deviations affect a minority of choices, it would be interesting in future research to introduce switching costs in models that account for sunk costs fallacy and other features of decision-making, as reference point, and to develop analytical predictions on the role of switching costs in these models.

6. Conclusions

Our work contributes to the field of competition in markets, testing experimentally the interplay between two different market frictions, search and switching costs, in affecting individual behavior and hence their potential impact on market outcomes. Our predictions relies on an analytical framework developed by Wilson (2012); we show that the search strategy has a more crucial role than the switch strategy in individual decision-making; indeed, not only, according to Wilson model, the search cost has a greater deterrent impact on search than the switch costs, but also the sub-optimality connected to search behavior are the major source of sub-optimality in behaviour. Policies aiming to improve the competitiveness of markets influencing individual decision-making should primarily focus on the search costs and the other aspects connected to search, as for example how the costs connected to search are presented to the consumers, in order to gain effectiveness. Furthermore, our analysis highlights the importance of considering risk-aversion in theoretical modelling as well as in empirical testing, and it suggests that some paths for improving the modelling of search and switching costs: the effort to introduce more realistic decision-making process into search models (e.g., Schunk, 2009) should be extended also to the search and switch costs framework as our findings suggests that there is an interplay between these costs and feature of the decision-making as sunk cost fallacy; although the deviations that we found with respect to Wilson model do not contradict our main conclusions, deepening their possible systematic role in decision-making could sheld light on the further interplay that between search and switch costs that the current theoretical framework is not able to capture.

References

Abrams, E., Sefton, M., & Yavas, A. (2000). An experimental comparison of two search models. *Economic Theory*, *16*, 735–749.

Braunstein, Y. M., & Schotter, A. (1982). Labor market search: An experimental study. *Economic inquiry*, *20*, 133–144.

Brennan, T. J. (2007). Consumer preference not to choose: methodological and policy implications. *Energy policy*, *35*, 1616–1627.

Cason, T. N., & Friedman, D. (2002). A laboratory study of customer markets. *Advances in Economic Analysis & Policy*, *2*.

Davis, D. D., & Holt, C. A. (1996). Consumer search costs and market performance. *Economic Inquiry*, *34*, 133–151.

Diamond, P. A. (1971). A model of price adjustment. *Journal of economic theory*, *3*, 156–168.

Farrell, J., & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization*, *3*, 1967–2072.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, *10*, 171–178.

Giulietti, M., Price, C. W., & Waterson, M. (2005). Consumer choice and competition policy: a study of uk energy markets. *The Economic Journal*, *115*, 949–968.

Goettler, R. L., & Clay, K. (2011). Tariff choice with consumer learning and switching costs. *Journal of Marketing research*, *48*, 633–652.

Hey, J. D. (1981). Are optimal search rules reasonable? and vice versa?(and does it matter anyway?). *Journal of Economic Behavior & Organization*, *2*, 47–70.

Honka, E. (2014). Quantifying search and switching costs in the us auto insurance industry. *The RAND Journal of Economics*, *45*, 847–884.

Kogut, C. A. (1990). Consumer search behavior and sunk costs. *Journal of Economic Behavior & Organization*, *14*, 381–392.

Luco, F. (2019). Switching costs and competition in retirement investment. *American Economic Journal: Microeconomics*, *11*, 26–54.

Moellers, C., Stühmeier, T., & Wenzel, T. (2016). *Search costs in concentrated markets: An experimental analysis*. Technical Report DICE Discussion Paper.

Morgan, J., Orzen, H., & Sefton, M. (2006). An experimental study of price dispersion. *Games and Economic Behavior*, *54*, 134–158.

Polyakova, M. (2016). Regulation of insurance with adverse selection and switching costs: Evidence from medicare part d. *American Economic Journal: Applied Economics*, *8*, 165–95.

Schram, A., & Sonnemans, J. (2011). How individuals choose health insurance: An experimental analysis. *European Economic Review*, *55*, 799–819.

Schunk, D. (2009). Behavioral heterogeneity in dynamic search situations: Theory and experimental evidence. *Journal of Economic Dynamics and Control*, *33*, 1719–1738.

Shcherbakov, O. (2016). Measuring consumer switching costs in the television industry. *The RAND Journal of Economics*, *47*, 366–393.

Waterson, M. (2003). The role of consumers in competition and competition policy. *International journal of industrial organization*, *21*, 129–150.

Wilson, C. M. (2012). Market frictions: A unified model of search costs and switching costs. *European Economic Review*, *56*, 1070–1086.

Appendix A. Instructions

Welcome to this experiment. Thank you for coming. These Instructions are to help you to understand what you are being asked to do during the experiment, and how you can earn money from it. This will be paid to you in cash after you have completed the experiment.

In this experiment there is a participation fee of £2.50, which will be added to whatever you earn in the experiment.

Please turn off your mobile phone and please do not talk with others for the duration of the experiment. If you have a question please raise your hand and one of the experimenters will answer your question in private.

The structure of the experiment

You will be presented with 80 independent problems. All have the same structure. In each problem you will earn points. At the end of the experiment one problem will be randomly selected for payment: the points earned in the selected problem will be converted into pounds as follows:

1 point= £0.65

To this will be added the participation fee of £2.50. You will be paid in cash and be able to leave immediately.

The nature of each problem

You should imagine that there are five boxes in front of you, each containing an offer. These offers consist of a number of points; **all offers will be between and including 8 and 22 points, rounded to the second decimal place.** All values between and including 8 and 22 are equally likely. Note that the offers are randomly generated: the number of points in a box is independent from the number of points in any other box. One of the boxes will initially be open and you will be able to see the offer inside it. We call this the initial offer. The other boxes will be initially closed, but you will be able to open any box and see the offer inside it.

Opening other boxes

In case you decide that you want to open other boxes and see the offers inside them, you will be able to do so. You can open as many as you like. Opening any box will cost you c points. Notice that you do not have to pay to see the initial offer: its box will be already open.

Acceptance of an offer

When you have opened as many boxes as you want, you can stop opening boxes, and can accept any offer 2 that you have obtained. When you stop, the number of points that you will earn for that problem will depend upon the number of boxes that you have opened – which we will denote by n – and the offer that you accept. It will be determined as follows:

If you accept the initial offer, points earned = initial offer – cn.

(Note that if you accept the initial offer without opening any other boxes then the number of boxes that you have opened, n, will be zero.)

If you accept any other offer, points earned = non-initial offer – cn – s.

Here s is the cost of accepting any non-initial offer.

The cost for opening any box, c, and the cost of accepting a non-initial offer, s, vary across problems. The value of these parameters in each problem will be shown on the screen in each problem. Please note that once you finish a problem the new one will not start until every participant has finished that problem.

Final Payment

After all of you have completed all 80 problems, the experiment itself will be over. One of the 80 problems will be selected at random. Your earned points in that problem will be recalled, and shown to you on the screen: you will be paid the amount of pounds corresponding to the number of points earned:

*pounds earned= points earned*0.65 plus a participation fee of £2.50*

Before proceeding to the payment you will be asked to answer to a short questionnaire on the screen where you have to give some information about yourself, but not your name. Indeed, the data analysis of the experiment will be absolutely anonymous: the experimenter will not able to connect your choices to you.

Here is an example

This is an example to familiarise yourself with the structure of the problems. Suppose c, the cost of opening any box and seeing the offer inside, is 1.00 point, and s, the cost of accepting any non-initial offer, is 0.50 points. Suppose the five offers, in points, are [9.15, 8.70, 21.35, 17.90, 11.30]. The initial offer is 9.15 points. Initially you will be able to see only the initial offer; you will see a screen such as the one in **Figure 1**: the values of c and s are stated on the screen and you have the possibility to accept the initial offer, 9.15, by clicking on the red button "Accept Initial Offer" or to open other boxes by clicking on the red button "Open Another Box". If you decide to open other boxes, they will be opened sequentially. The points you earn will depend on what you do:

If you decide not to open any boxes and hence accept the initial offer, your points earned =9.15.

If you decide to open just one box, the offer in that box is 8.70. You can accept either the initial offer or the second offer, as shown in **Figure 2**.

If you accept the initial offer, your points earned = 9.15 − 1.00 = 8.15.
If you accept the second offer, your points earned = 8.70 − 1.00 − 0.50 = 7.20.

If you decide to open just two boxes, the offers in those boxes are 8.70 and 21.35. You can accept either the initial offer, the second offer or the third offer. If you accept the initial offer, your points earned = 9.15 − 2*1.00 = 7.15.

If you accept the second offer, your points earned = 8.70 – 2*1.00 – 0.50 = 6.20.

If you accept the third offer, your points earned = 21.35 – 2*1.00 – 0.50 = 18.85.

If you decide to open just three boxes, the offers in those boxes are 8.70, 21.35 and 17.90. You can accept either the initial offer, the second offer, the third offer or the fourth offer.

If you accept the initial offer, your points earned = 9.15 – 3*1.00 = 6.15.

If you accept the second offer, your points earned = 8.70 – 3*1.00 – 0.50 = 5.20.

If you accept the third offer, your points earned = 21.35 – 3*1.00 – 0.50 = 17.85.

If you accept the fourth offer, your points earned = 17.90 – 3*1.00 – 0.50 = 14.40.

If you decide to open all four boxes, the offers in those boxes are 8.70, 21.35, 17.90 and 11.30. You can accept either the initial offer, the second offer, the third offer, the fourth offer or the fifth offer.

If you accept the initial offer, your points earned = 9.15 – 4*1.00 = 5.15.

If you accept the second offer, your points earned = 8.70 – 4*1.00 – 0.50 = 4.20.

If you accept the third offer, your points earned = 21.35 – 4*1.00 – 0.50 = 16.85.

If you accept the fourth offer, your points earned = 17.90 – 4*1.00 – 0.50 = 13.40.

If you accept the fifth offer, your points earned = 11.30 – 4*1.00 – 0.50 = 6.80.

After you make your choice, your payment, if that problem would be randomly drawn at the end of the experiment, will be shown on the screen. Figure 3 gives you an example of what you would see on the screen at the end of the problem if you accepted the third offer after opening 2 boxes.

Before starting the experiment you will be asked to answer some questions on the screen to check that you understood the instructions. Then, before starting the 80 problems, you will play a practice problem. The practice problem will not be considered for the final payment.

If you have any questions, please raise your hand and one of us will come and

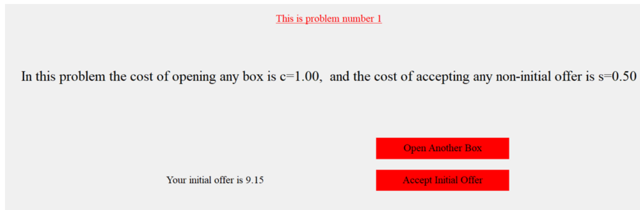

Figure A.1: Figure 1 in the instructions

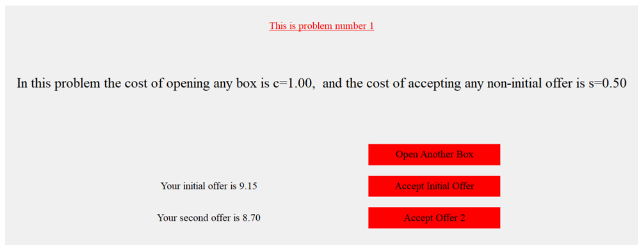

Figure A.2: Figure 2 in the instructions

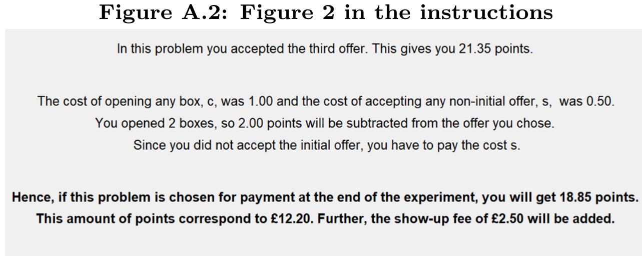

Figure A.3: Figure 3 in the instructions

answer your question. Thank you for participating in this experiment.

Irene Maria Buso John Hey

February 2019

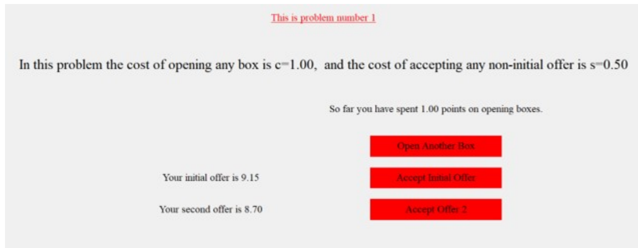

Figure A.4: Figure 2 in the instructions

In the *Cost Display* treatment in the *main experiment* the instruction let the participant aware of the cost display during the experiment; this is shown in the instruction's figures as well as in Figure A.4.

The instructions of the Extension Experiment have the same structure of the *Main Experiment* but the number of offers and the example are adapted to 10 offers.

Appendix B. Full regression tables

This is the list of control variables used in the regression analyses. *Cost Display* is a dummy variable equal to 1 when the subject is shown the cumulative search cost during the search on the screen, 0 otherwise. *Sex* is a dummy variable equal to 1 when the subject is female, 0 otherwise. *Period* is the period number, it goes from 2 to 81 as the initial trial period is not considered in the regression analyses. *Age* is the age in years. *Statistics* is the level of statistical knwoledge: 1="Basic knowledge (from school)"; 2="Advanced knowledge (basic courses, e.g. at the University)"; 3="Deeper knowledge (specialized courses, e.g. at the University)"; 4="Other". *Degree Level* is level of the highest degree they are currently studying, and it is 1="Qualification for university entrance"; 2="Bachelor"; 3="Master"; 4="PhD"; 5="Other"; 6="Not a student". *Degree Major* is 1="Business"; 2="Economics"; 3="Law"; 4="Psychology"; 5="Sociology"; 6="Other Major"; 7="Not a Student".

Table B.13 reports the regression in Table 2 with controls.

Table B.13: Comparative Static 1,2 and 3. Full regression.

	(1)	*(2)*
	Start Search	*Initial Points Accepted*
c	-1.766***	-0.909***
	(0.112)	(0.227)
s	-0.319***	-0.299***
	(0.0244)	(0.0556)
interaction c & s	-0.0634*	-0.144*
	(0.0356)	(0.0822)

Continued on next page

Table B.13 – *Continued from previous page*

	Start Search	*Initial Points Accepted*
Initial Offer	-0.408***	-
	(0.00826)	
Cost Display	0.505**	0.313
	(0.249)	(0.342)
Session	-0.152***	-0.136*
	(0.0581)	(0.0791)
Period	0.00332***	0.00546***
	(0.000835)	(0.00183)
Age	-0.0142	-0.00250
	(0.0169)	(0.0228)
Degree Major		
2	0.135	-0.450
	(0.300)	(0.413)
3	-0.183	-0.0791
	(0.299)	(0.404)
4	0.434	-0.544
	(0.362)	(0.511)
5	0.856**	0.939**
	(0.337)	(0.469)
6	0.258	0.358
	(0.173)	(0.237)
Degree Level		
2	0.0635	1.003*
	(0.397)	(0.559)

Continued on next page

Table B.13 – *Continued from previous page*

	Start Search	*Initial Points Accepted*
3	0.264	1.257**
	(0.409)	(0.575)
4	-0.329	0.678
	(0.452)	(0.629)
5	-0.312	0.0464
	(0.604)	(0.824)
Statistics		
2	0.202	0.501***
	(0.139)	(0.190)
3	0.175	0.740**
	(0.220)	(0.299)
Sex	0.143	-0.0697
	(0.131)	(0.180)
Constant	8.587***	18.56***
	(0.579)	(0.782)
$\hat{\sigma}^2_c$	0.583***	0.651***
	(0.117)	(0.223)
$\hat{\sigma}^2_s$	0.0179***	0.012***
	(0.00473)	(0.009)
$\hat{\sigma}^2_{const}$	0.307***	0.380***
	(0.0565)	(0.111)
Observations	9920	3323
	Standard errors in parentheses	* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.14 reports the regression in Table 3 with controls.

Table B.14: Comparative Statics 4,5 and 7. Full regression.

	(1) *n of Non-Local Searches*	*(2)* *n of Non-Local Searches (consistent choices only)*	*(3)* *Initial*
c	-2.739***	-3.066***	0.891***
	(0.112)	(0.126)	(0.231)
s	-0.0598***	-0.0116	0.520***
	(0.0220)	(0.0297)	(0.0370)
Initial Offer	0.0130**	0.0887***	0.523***
	(0.00656)	(0.00944)	(0.0224)
Period	0.00425***	0.00449***	-0.000558
	(0.000903)	(0.00120)	(0.00181)
Session	-0.0149	-0.00711	0.0198
	(0.0719)	(0.0733)	(0.0404)
Cost Display	-0.0826	-0.0421	-0.135
	(0.307)	(0.313)	(0.174)
Age	0.00483	-0.000833	-0.000195
	(0.0211)	(0.0215)	(0.0124)
Degree Major			
2	-0.169	-0.184	0.128
	(0.378)	(0.386)	(0.220)
3	-0.163	-0.182	0.557***
	(0.367)	(0.372)	(0.190)
4	-0.520	-0.411	0.268

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Table B.14 – *Continued from previous page*

	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
	(0.451)	(0.461)	(0.283)
5	0.114	0.111	0.308
	(0.411)	(0.422)	(0.233)
6	0.0297	0.0923	0.258**
	(0.215)	(0.220)	(0.123)
Degree Level			
2	0.0745	0.136	-0.0541
	(0.502)	(0.511)	(0.267)
3	0.116	0.287	0.130
	(0.516)	(0.526)	(0.274)
4	-0.419	-0.285	-0.200
	(0.570)	(0.584)	(0.330)
5	-0.463	-0.649	0.282
	(0.761)	(0.780)	(0.483)
Statistics			
2	0.188	0.181	0.0795
	(0.172)	(0.176)	(0.102)
3	0.397	0.366	-0.0194
	(0.274)	(0.278)	(0.152)
Sex	-0.205	-0.102	0.109
	(0.162)	(0.165)	(0.0901)
Interaction c & s	0.0174	0.0304	-0.0746
	(0.0398)	(0.0526)	(0.0902)
Offer 2			-0.116***

Continued on next page

Table B.14 – *Continued from previous page*

	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
			(0.0115)
Offer 3			-0.123***
			(0.0121)
Offer 4			-0.124***
			(0.0118)
Offer 5			-0.141***
			(0.0112)
Constant	3.975***	3.244***	-2.904***
	(0.704)	(0.724)	(0.535)
Observations	6597	5427	2712
	Standard errors in parentheses	* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$	

Table B.15: Regression on the number of non-local searches with inconsitent choices only.

	(1) *n of Non-Local Searches* *(inconsistent choices only)*
c	-0.45***
	(0.08)
s	-0.03*
	(0.02)

Continued on next page

Table B.15 – *Continued from previous page*

	n *of Non-Local Searches* *(inconsistent choices only)*
Initial Offer	-0.07***
	(0.005)
Period	0.0001
	(0.001)
Session	-0.07
	(0.04)
Cost Display	0.253
	(0.17)
Age	0.01
	(0.01)
Degree Major	
2	0.03
	(0.22)
3	-0.17
	(0.19)
4	-0.38
	(0.23)
5	0.32
	(0.22)
6	-0.09
	(0.12)
Degree Level	
2	0.69**

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Table B.15 – *Continued from previous page*

	n of Non-Local Searches (*inconsistent choices only*)
	(0.28)
3	0.63**
	(0.29)
4	0.77**
	(0.33)
5	0.73
	(0.46)
Statistics	
2	0.10
	(0.09)
3	0.03
	(0.16)
Sex	0.08
	(0.10)
Interaction c & s	-0.08**
	(0.03)
Constant	2.50***
	(0.40)
$\hat{\sigma}^2_c$	4.57e-38
	(6.37e-21)
$\hat{\sigma}^2_{const}$	0.115***
	(0.0223)
Observations	1170

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Table B.15 – *Continued from previous page*

	n *of Non-Local Searches*
	(inconsistent choices only)
Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$	

Table B.16 reports the regression in Table 5 with controls.

Table B.16: Comparative Static 1,2 and 3 in the *Extension* Experiment. Full regression.

	(1)	*(2)*
	Start Search	*Initial Offer Accepted*
c	-3.28***	-1.04
	(0.40)	(0.78)
s	-0.46***	-0.18
	(0.08)	(0.20)
interaction c & s	0.06	-0.55
	(0.26)	(0.59)
Initial Offer	-0.42***	-
	(0.02)	
Session	-0.19	-0.08
	(0.15)	(0.37)
Period	0.007***	0.015***
	(0.0016)	(0.003)
Age	-0.025*	0.023

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Table B.16 – *Continued from previous page*

	Start Search	*Initial Points Accepted*
	(0.015)	(0.037)
Degree Major		
2	0.19	-0.12
	(0.27)	(0.66)
3	0.13	-1.13
	(0.36)	(0.90)
4	1.118**	1.02
	(0.48)	(1.24)
5	0.30	-0.75
	(0.33)	(0.84)
6	0.23	-0.13
	(0.24)	(0.59)
7	0.77	-1.68
	(0.62)	(1.55)
Degree Level		
3	0.39**	-0.19
	(0.19)	(0.47)
4	-0.21	-0.46
	(0.22)	(0.55)
Statistics		
2	-0.16	-0.042
	(0.18)	(0.44)
3	-0.38	-0.14
	(0.24)	(0.61)
4	1.15**	1.17

Continued on next page

Table B.16 – *Continued from previous page*

	Start Search	*Initial Points Accepted*
	(0.47)	(1.22)
Sex	0.10	-0.25
	(0.15)	(0.35)
Constant	9.22	19.57
	(0.59)	(1.25)
$\hat{\sigma}^2_c$	2.04***	0.49
	(0.73)	(1.09)
$\hat{\sigma}^2_s$	0.01	0.07
	(0.01)	(0.07)
$\hat{\sigma}^2_{const}$	0.02	0.44
	(0.03)	(0.18)
Observations	3120	761

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.17 reports the regression in Table 6 with controls.

Table B.17: Comparative Statics 4,5 and 7 in the *extension* experiment. Full regression.

	(1)	*(2)*	*(3)*
	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
c	-13.43***	-15.22***	2.99**
	(0.82)	(0.91)	(1.42)

Continued on next page

Table B.17 – *Continued from previous page*

	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
s	-0.26	-0.21	0.54***
	(0.16)	(0.20)	(0.16)
Initial Offer	0.06***	0.16***	0.70***
	(0.02)	(0.03)	(0.08)
Period	0.02***	0.02***	0.001
	(0.003)	(0.004)	(0.005)
Session	-0.96**	-0.86**	0.28
	(0.42)	(0.38)	(0.26)
Age	-0.050	-0.07*	0.007
	(0.04)	(0.04)	(0.02)
Major			
2	1.08	0.92	0.43
	(0.77)	(0.69)	(0.53)
3	-0.21	-0.41	0.61
	(1.04)	(0.99)	(0.75)
4	1.47	2.08*	0.04
	(1.24)	(1.13)	(0.70)
5	0.97	1.65*	0.66
	(0.94)	(0.87)	(0.63)
6	0.34	0.50	0.59
	(0.68)	(0.61)	(0.46)
7	-2.69	-1.94	0
	(1.77)	(1.62)	(.)

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Table B.17 – *Continued from previous page*

	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
Degree Level			
3	-0.029	0.17	-0.13
	(0.53)	(0.48)	(0.32)
4	-1.05	-1.13*	-0.12
	(0.65)	(0.58)	(0.44)
6	0	0	1.150
	(.)	(.)	(1.296)
Statistics 2	0.19	0.28	-0.03
	(0.49)	(0.45)	(0.31)
3	-0.66	-0.65	-0.33
	(0.70)	(0.63)	(0.47)
4	0.44	1.62	0.388
	(1.24)	(1.18)	(0.77)
Sex	-0.85**	-0.57	0.040
	(0.41)	(0.37)	(0.28)
interaction c & s	0.54	0.47	0.47
	(0.57)	(0.72)	(1.02)
Offer 2			-0.03
			(0.02)
Offert 3			-0.05**
			(0.03)
Offer 4			-0.04
			(0.03)

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Table B.17 – *Continued from previous page*

	n of Non-Local Searches	*n of Non-Local Searches (consistent choices only)*	*Initial*
Offer 5			-0.07**
			(0.03)
Offer 6			-0.05**
			(0.03)
Offer 7			-0.05*
			(0.03)
Offer 8			-0.04
			(0.03)
Offer 9			-0.0331
			(0.0275)
Offer 10			0.01
			(0.03)
Constant	9.88***	9.11***	-10.10***
	(1.49)	(1.43)	(1.83)
$\hat{\sigma}^2_c$	10.11***	7.47*	
	(3.88)	(4.06)	
$\hat{\sigma}^2_{const}$	0.610***	0.296	2.32e-34
	(0.235)	(0.205)	(4.12e-18)
Observations	2359	1945	716

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.18: Inconsistent Choices *main* experiment. Full regression.

	(1) *Inconsistent*
c	-0.473***
	(0.106)
s	-0.0438*
	(0.0256)
Interaction c & s	-0.0294
	(0.0399)
Session	-0.0729
	(0.0585)
Cost Display	0.529**
	(0.250)
Period	-0.00133
	(0.000852)
Initial Offer	-0.0314***
	(0.00507)
Age	-0.0118
	(0.0174)
Degree Major	
2	-0.0538
	(0.315)
3	-0.342

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Table B.18 – *Continued from previous page*

	Inconsistent
	(0.299)
4	0.0906
	(0.356)
5	0.267
	(0.331)
6	0.128
	(0.174)
Degree Level	
2	0.128
	(0.424)
3	0.348
	(0.438)
4	0.562
	(0.478)
5	-0.130
	(0.643)
Statistics	
2	0.0653
	(0.138)
3	-0.305
	(0.226)
Sex	0.415***
	(0.134)
Constant	-0.586
	(0.585)

Continued on next page

Table B.18 – *Continued from previous page*

	Inconsistent
$\hat{\sigma}_c^2$	0.258***
	(0.0795)
$\hat{\sigma}_s^2$	0.00770*
	(0.00403)
$\hat{\sigma}_{const}^2$	0.307***
	(0.0590)
Observations	7208

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix C. Risk attitudes in Wilson's Model

From Wilson 2012, the risk-neutral agent solves

$$\epsilon - p^* = -c + \int_x^{\overline{\epsilon}} (\epsilon' - p^*) g(\epsilon') d\epsilon' + \int_{\underline{\epsilon}}^{x} (\epsilon - p^*) g(\epsilon') d\epsilon' \tag{C.1}$$

where $x \equiv \epsilon$.

We now extend equation (C.1) in order to accont for risk attitudes:

$$u(\epsilon - p^* - nc) = \int_x^{\overline{\epsilon}} u(\epsilon' - p^* - nc - c) g(\epsilon') d\epsilon' + \int_{\underline{\epsilon}}^{x} u(\epsilon - p^* - nc - c) g(\epsilon') d\epsilon' \tag{C.2}$$

Assuming a CARA utility function $u(\epsilon) = \exp^{-r\epsilon}$ and a uniform distribution for $g(\epsilon) = \frac{1}{\overline{\epsilon} - \underline{\epsilon}}$ and recaling that for the purpose of our experiment we can assume that $p^* = 0$, equation (C.2) can be rewritten as follows :

$$\exp^{-r\epsilon} = \frac{1}{\overline{\epsilon} - \underline{\epsilon}} [\int_x^{\overline{\epsilon}} \exp^{-r(\epsilon' - nc - c)} d\epsilon' + \int_{\underline{\epsilon}}^{x} \exp^{-r(\epsilon - nc - c)} d\epsilon'] \tag{C.3}$$

We solve these two integrals separately.

The first integral is:

$\int_x^{\overline{\epsilon}} \exp^{-r(\epsilon' - nc - c)} d\epsilon' = [-\frac{\exp^{-r(\epsilon' - nc - c)}}{r}]_x^{\overline{\epsilon}} = -\frac{1}{r} \exp^{-r\overline{\epsilon}} \exp^{-rnc} \exp^{-rc} + \frac{1}{r} \exp^{-rx} \exp^{-rnc} \exp^{-rc} = \frac{1}{r}(\exp^{-rx} - \exp^{-r\overline{\epsilon}}) \exp^{-rnc} \exp^{-rc}$

The second integral is:

$\int_{\underline{\epsilon}}^{x} \exp^{-r(\epsilon - nc - c)} d\epsilon' = \exp^{-r(\epsilon - nc - c)} \int_{\underline{\epsilon}}^{x} 1 d\epsilon' = \exp^{-r(\epsilon - nc - c)} [\epsilon']_{\underline{\epsilon}}^{x} = \exp^{-r(\epsilon - nc - c)}(x - \underline{\epsilon}) = (x - \underline{\epsilon}) \exp^{-rx} \exp^{-rnc} \exp^{-rc}$

where $x \equiv \epsilon$

Substituting these integrals into equation(3) equation, we get:

$\exp^{-rx} \exp^{rnc} = \frac{1}{\overline{\epsilon} - \underline{\epsilon}} [\frac{1}{r}(\exp^{-rx} - \exp^{-r\overline{\epsilon}}) \exp^{rnc} \exp^{rc} + \exp^{rnc} \exp^{rc} \exp^{-rx}(x - \underline{\epsilon})]$

Dividing by $\exp^{rnc}$, we get:

$\exp^{-rx} = \frac{1}{\overline{\epsilon}-\underline{\epsilon}}[\frac{1}{r}(\exp^{-rx} - \exp^{-r\overline{\epsilon}})\exp^{rc} + \exp^{rc}\exp^{-rx}(x - \underline{\epsilon})]$

$\implies (\overline{\epsilon} - \underline{\epsilon})\exp^{-rc} = \frac{1}{r}(1 - \exp^{r\overline{\epsilon}}\exp^{rx}) + (x - \underline{\epsilon})$

$\implies x = (\overline{\epsilon} - \underline{\epsilon})\exp^{rc} - \frac{1}{r} + \frac{1}{r}\exp^{-r\overline{\epsilon}}\exp^{rx} + \underline{\epsilon}$

We finally get the same expression for the reservation utility of the risk averse agent, $\hat{x}$ that we have presented in the main text of this paper. This is the expression of $\hat{x}$ that we used in our MATLAB code.

Appendix D. Stochastic specification of the Wilson's Model

We denote the cumulative distribution function of the Beta distribution by $G(.)$. Note that it is degenerate if $\hat{X}$ is either 0 or 1.

- First, the DM needs to decide whether to start search. Starts if $\hat{x} > \epsilon_1 + s$. So the contribution to the likelihood, forgetting for the moment trembles, is:

  $G((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon}))$, if the DM does not start searching
  $1 - G((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon}))$if the DM does start searching.

  But the DM might tremble with probability t. So we get as contributions to the likelihood:

  $(1-t)G((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon})) + t(1 - G((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon})))$, if the DM does not start searching.
  $tG((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon})) + (1-t)(1 - G((\epsilon_1 + s - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon})))$ if the DM starts searching.

- If the DM has started, he or she needs to decide whether to continue. Searches for the i^{th} time if $\hat{x} > \epsilon_i$. So the contribution to the likelihood (forgetting for the moment trembles) is:

  $G((\epsilon_i - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon}))$ if the DM stops searching after the $i - 1^{th}$ search.

  $1 - G((\epsilon_i - \underline{\epsilon})/(\overline{\epsilon} - \underline{\epsilon}))$ if the DM continues searching after the $i - 1^{th}$ search.

  We also consider the cases when G(.) is degenerate. One case is when $\hat{X} = 1$, then the consumer should search all the market, that is for all epsilon lower than the maximum[20]. If we again assume a tremble, the contribution to the likelihood if $\hat{X} = 1$ and the individual stops searching before the last is t.

Another case when G(.) is degenerate is when $\hat{X} = 0$. In this case, the individual should not start searching, and each search that he or she does is a tremble.

So we have, that the contribution to the likelihood of searching the i^{th} offer, ϵ_i, when the $i - 1^{th}$ search is not over the final offer is:

If $\hat{X} > 0$ and $\hat{X} < 1$

$(1-t)G((\epsilon_i-\underline{\epsilon})/(\bar{\epsilon}-\underline{\epsilon}))+t(1-G((\epsilon_i-\underline{\epsilon})/(\bar{\epsilon}-\underline{\epsilon})))$ if the DM stops searching after the discovering ϵ_i.

$tG((\epsilon_i-\underline{\epsilon})/(\bar{\epsilon}-\underline{\epsilon}))+(1-t)(1-G((\epsilon_i-\underline{\epsilon})/(\bar{\epsilon}-\underline{\epsilon})))$ if the DM keeps searching after the discovering ϵ_i.

If $\hat{X} = 1$ t if the DM stops searching before having searched all the market.

$1 - t$ if the DM search all the market.

If $\hat{X} = 0$

t if the DM start searching

$1 - t$ if the DM do not start searching.

- When the individual stops searching, he or she should choose the best offer, taking into account the switch cost. If they do, there is no error and the contribution to the likelihood is (1-t). If they do not accept the best offer,

[20] I am assuming that no offer exactly equal to either extreme is ever observed.

they tremble and the contribution to the likelihood is t. We estimated the parameters also considering the tremble parameter concerning the best offer choice as distinguished from the one involved in the search process. The estimations of the parameters in this case are: risk aversion equal to 0.34, precision equal to 18.60, the tremble in search is equal to 0.089 and the tremble in the final optimal choice is 0.075.