Obfuscation and Honesty Experimental Evidence on Insurance Demand with Multiple Distribution Channels

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Abstract

This paper aims to shed light on the dilemma faced by insurance purchasers faced with multiple distribution channels. Should the consumer herself choose from a large set of insurance policies or rather delegate a part her decision to an intermediary who is more or less honest? We consider decisions based on a number of real-world insurance distribution channels with different information frames. Beliefs about intermediary honesty are the main determinants of individual choice. In addition, the obfuscation of information is the main source of inefficiency in decision-making, particularly regarding the characteristics of the insurance contracts chosen by consumers.

Keywords: behavioral economics, distribution channels, honesty, insurance, intermediation,obfuscation, search costs.

1 Introduction

The internet has significantly affected purchasing behavior by changing access to information. No industry has been immuned to this considerable change, including more recently the insurance sector, see e.g. Cappiello [2018]. In principle, greater access to market information allowing the better comparison of offers is a good news for consumers. In the past ten years, we have seen the erosion of the traditional distribution channels of brokers and tied-agents, see e.g. technical reports of FFA for the French market. However, these channels continue to co-exist with new channels such as cyber-brokers and online insurance websites. Consumers therefore continue to value physical intermediation.

This is partly explained by the complexity of insurance products, leading to obfuscation. Obfuscation here reflects the limited discernment of agents due to excess information or the introduction of a great deal of irrelevant information. Physical intermediaries reduce this obfuscation by offering comparisons and advice. However, physical intermediaries also have their own financial incentives from insurers and consumers demand for their services. The extent to which intermediaries are honest and how consumers perceive this honesty are therefore central in the delegation decision.

Consumers will delegate only if they believe others to be sufficiently honest. The consumer decision is thus based on a trade-off between finding the appropriate information in a context of obfuscation and obtaining good information from more or less honest intermediaries.

The aim of this paper is to understand how consumers choose their insurance contracts in this kind of multichannel environment. Consumer decision-making is complex as, in addition to insurance-contract choice, they have to choose their search strategy. We here provide some insights into how this choice reveals information about the customer profile (price elasticity, risk profile etc.). The results underline the importance for firms of managing their distribution strategy and contract offers among heterogeneous consumers in order to screen between them.

We take into account consumers potential search costs to access information when considering delegation and information-gathering. These costs are defined as the time, effort and money expended by a consumer who searches for a product or service. Our goal here is not to measure these individual search costs, contrary to Brynjolfsson and Smith [2000]. Search costs are considered to be neutral and exogenous, such that the expected search cost to find the optimal policy is the same for each distribution channel. The presence of search costs ensures that individual exploration choices are taken conscientiously. We also do not consider the effect of search costs on the market price equilibrium, contrary to Diamond [1971], Brown and Goolsbee [2002], Baye et al. [2004] and Branco et al. [2012]), and focus on the demand side of the market with exogenously-defined offers.

Psychological theory suggests that greater available information and choice should improve the quality of decisions by informing consumers of all of the possibilities. However, S. Iyengar and Lepper [2001] carry out a number of different behavioral experiments and show that this assumption does not necessarily hold: the desire for choice is not unlimited. This conclusion also pertains in the experimental analysis in Schram and Sonnemans [2011] regarding the choice of health insurance. They find that when there are many alternatives, subjects only consider a smallest part of the available information and carry out a process of elimination based on limited characteristics. Hence, search costs and delegation choice affect the quantity of information available for choice, which in turn might lead to focal point and anchoring effects due to obfuscation (see e.g. Gabaix et al. [2006], Ellison and Ellison [2009], and Ke et al. [2016]).

Search costs and obfuscation can lead to delegation by consumers. Insurance intermediaries are meant to follow deontological rules and propose optimal contracts, as they are paid to do so. However, the relationship between the consumer and physical intermediaries underlines the role of honesty. This exchange game affects trust, which might at first lead us to think of trust-game analysis (Berg et al. [1995]). However, their exchange game contains no normative rules (i.e. there is no rule that individuals should transfer money or reward transfers). Thus, this approach does not allow for objective deviation to be controlled for, as each individual will have a subjective view of the behavior to be adopted, which could depend on inequality aversion (Glaeser et al. [2000]).

The insurance market, as mentioned above, has intermediaries who sell advice, implying a normative rule. The presence of this implicit rule therefore leads us to appeal to more recent concepts of honesty (Fischbacher and Föllmi-Heusi [2013]) and beliefs about others honesty (Hugh-Jones [2016]). Although normative rules exist for insurance intermediation, Cummins and Doherty [2006] note the importance of insurers' financial incentives on their advice. Houser et al. [2012] find greater dishonesty when people have been treated unfairly. Inequality observed by the intermediary between different bonus levels can arouse an unfair feeling because from her point of view, these inequalities are groundless. This result is confirmed by Galeotti et al. [2017], showing that financial incentives influence intermediaries honesty. Intermediary behavior is a concrete issue and regulatory concern, as the IDD (Insurance Distribution Directive) illustrates. This new European directive comes into force in October 2018, and aims to monitor insurers financial incentives more strictly.

As honesty is difficult to observe in the field, we here elicit honesty and belief about others honesty in a laboratory experiment. The experimental approach allows us to measure individual risk aversion, which affects decisions in uncertain contexts such as insurance.

All of the above concerns appear in our experiment. We find that honesty beliefs are important in the choice of distribution channel. Subjects who expect honesty ask for more advice, in particular when the probability of loss is higher. Risk-averse individuals do not directly visit insurers and prefer to explore the market via brokers or cyber-brokers. We also see that intermediary dishonesty leads subjects to change channel, in particular when they initially expect honesty.

We identify two opposing search strategies: 'saving search (costs)' and 'deep search'. Risk-averse subjects avoid 'saving search', especially as the probability of loss rises. Regarding contract choice, we find that only the probability of loss has a significant positive effect on coverage choice. However, we also find focal-point and anchoring effects with respect to the quantity of information. Obfuscation leads subjects to choose their contract by comparing prices (i.e. the focal-point effect). Subjects also take into account the gaps between contract prices, with the average contract price acting as a benchmark in purchasing decisions (i.e. the anchoring effect).

We also find that obfuscation leading to focal point effect is a source of inefficient choices. When the quantity of information increases, the probability to choose the lowest price increases which lead to non-efficient choices. This is particularly true when consumers decide to explore only by themselves though comparator channel. However, intermediaries deviation is also a source of inefficiency choices although detection of deviation leads to more efficient choices. Thus, the trade-off between delegation and self-exploration is essentially supported by beliefs in others' honesty when market exploration is costly and information is not easy to compare.

Last, as intermediaries have their own financial incentives, we find considerable deviation (i.e. they do not propose the best contract), especially when it is profitable to do so. Wealth and the nature of risk do not affect deviation. However, deviation is considered to be risky, as risk-averse intermediaries deviate less. We also find a correlation between honesty and deviation in advice in the insurance market at the session level, where more honest intermediaries are more likely to suggest the optimal contract.

The remainder of the paper is organized as follows. We set out the experimental design in Section 2, and Section 3 briefly summarizes the procedure. Section 4 then describes the detailed results, and Section 5 concludes.

2 Experimental design

We designed an experiment to identify the determinants of insurance choice, including intermediaries and search costs (the cost of exploration). After controlling for individual risk attitudes and beliefs about other's honesty, the experiment allows us to investigate the consumer's exploration decision and contract choice. The elicitation of risk aversion is used to parameterize the design of the contract choice. The instructions for each part of the experiment as well as screenshots of the interface can be found in Appendix A. Subjects are divided into two groups, A and B, and remain in the same group throughout the experiment.

2.1 The elicitation of honesty and beliefs about others' honesty

In this first part, we propose an original experiment in order to elicit individual honesty and beliefs about other's honesty. We do so via the exchange of coins between a wallet and a padded envelope.

Before the session starts, a wallet is put on the table of each participant. This wallet either contains 10 coins of 0.50€ and a small card showing the result of 10 independent draws, or nothing. The 10 draws are of a red or green ball without replacement from a bag containing 7 red balls and 7 green balls (so that there are five possible draws, corresponding to 3, 4, 5, 6 or 7 red balls).

The content of each wallet establishes the participant's group. If the wallet is not empty, the subject is in group B. They are asked to discreetly apply the following rule: for each green ball drawn on the card they can take 0.50€ from the wallet and put it in the padded envelope: the coins in the envelope represent their gains for this part of the experiment. The Euros remaining in the wallet should then correspond to 0.50€ times the number of red balls. However, participants are informed that no-one in the room, including other participants and the experimenter, will check if they follow this rule. The wallets cannot be identified within individuals, and are all put in the same bag at the end of this part of the experiment.

If the wallet is empty, the subject is in group A. We show on their computer screen the different draws that were distributed to the B subjects. They then indicate for each draw how many Euros they think that the B subjects left in their wallets. The gain of the A participants in this part comes from the random selection of one of these draws, with their earnings being 5 Euros minus the estimation error.

2.2 The elicitation of risk aversion

In this part, all gains are expressed in ECU (Experimental Currency Units), which are converted at the end of the session using the following rate: 50 ECU = 1€. Risk preferences are measured for all subjects in the gain and loss domains. We use the Multi Price List (MPL) method suggested by Holt and Laury [2002] and convert dollars into ECU.

Subjects make two series of 10 decisions between alternatives 'A' and 'B'. The first 10 questions concern risk attitudes towards gains. For example, subjects have to choose between receiving 50 ECU with a probability of 10% and 20 ECU with a probability of 90% (alternative 'A') and 85 ECU with a probability of 10% and 5 ECU with a probability of 90% (alternative 'B').

There are then questions about risk attitudes towards losses. We attribute to each subject and for each question an initial endowment. They then have to choose one more or less risky alternative, for instance between losing 50 ECU of their 100 ECU (the initial endowment) with a probability of 10% and losing 80 ECU with a probability of 90% (alternative 'A') and losing 15 ECU of their 100 ECU with a probability of 10% and losing 80 ECU with a probability of 95% (alternative 'B').

It can be argued that the house-money effect (Thaler and Johnson [1990]) makes participants more willing to take risks. However, Etchart-Vincent and l'Haridon [2011] compare subjects' risk attitudes in three payment conditions: a real loss condition with a random lottery, 'losses-from-an-initial-endowment' and a hypothetical-loss condition. They find no significant difference between these three payment conditions in the loss domain, supporting our approach.

In addition to comparing risk aversion in the gain and loss domains, we choose payoffs such that the expected payoff for each level of the gain and loss question are the same. In other words, if alternative 'A' in the first questionnaire is 'win 10 ECU with a probability of 10%', then alternative 'A' in the second is 'from 100 ECU lose 90 ECU with a probability of 10%'.

We measure participants' risk aversion by their first switch from a safe to a risky option, for both series of questions. For instance, a subject who switches at Question 5 is considered to be more risk-averse than one who switches at Question 2.

2.3 Main game

In the main game, participants retain their type from the first part of the experiment (A or B): A-type participants now play the role of insurance customers while B-type participants are 'human' intermediaries. The game is repeated for eight periods (called rounds), including two trial rounds.

A participants select an insurance contract in each round that protects against a known loss with known risk (probability). Each contract includes a fixed premium and a deductible paid in the case of loss. B-type participants can provide advice to A-type participants. The A's can call on human intermediaries to obtain information about the contracts. In this case, one of the B's is chosen randomly to provide advice. We explain below the precise nature of this interaction.

2.3.1 The design of the exploration game

The A's choose one contract in each round: they cannot remain uninsured. In each round, they have an initial level of wealth and a probability and amount of loss. These elements can vary by period. There are eight different available contracts grouped into four menus of two contracts each (A, B, C and D). These different menus represent the insurance companies on the market. These contracts are hidden at the beginning of each round, and to obtain information on them A's have to explore the market. To do so, they have an exploration allowance that is equally re-endowed at the beginning of each round. This credit is run down for each exploration action, and the unused exploration credit forms part of A's earnings. A screenshot of the instructions at the beginning of each round appears in Appendix A.

Participants can explore the market directly by choosing one of the four 'company' menus. This corresponds to individual sequential research, such as visiting insurance vendors or websites one by one. To do so, the A's pay 12 ECU (debited from their exploration credit). Once they access the information about the two contracts on the menu, they can ask for a recommendation for 4 ECU (also deducted from the exploration credit) corresponding to time spent with a tied-agent or a call-center for advice about the products from one unique company. In this case, one of the B's is selected to give advice.

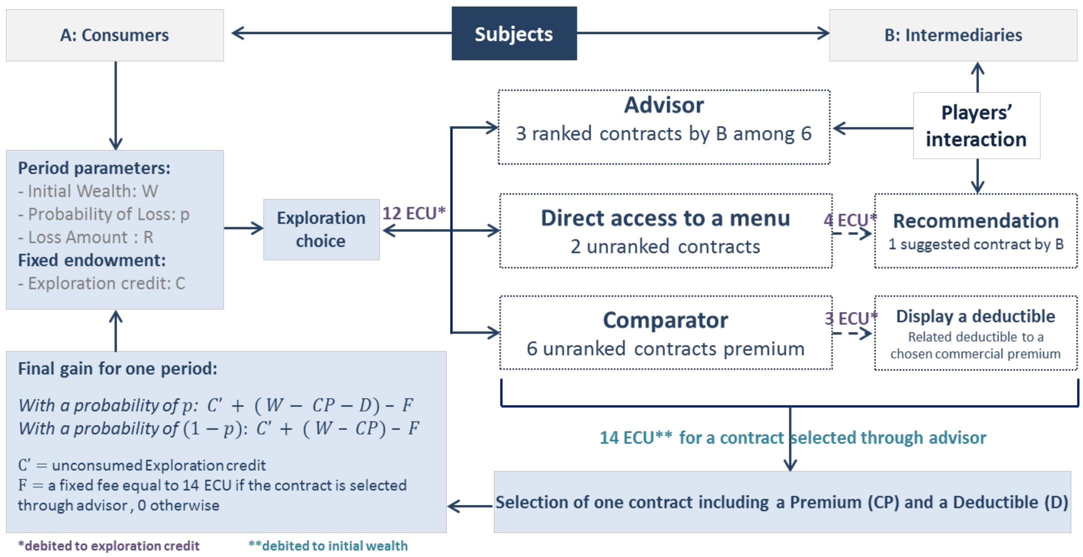
This B-type participant receives additional information about the contracts: their screen shows a ranking of the two contracts depending on the policy features and A's risk attitude. We explain below how this ranking is produced. In addition, there is a bonus for each contract that is paid to B if A underwrites this contract via B's intermediation. The bonuses are not paid by A. B decides which contract to suggest according to this information. The A-type participants do not know the bonus information.

Another possibility for A-type subjects is to look for an advisor (i.e. a B) corresponding to a broker. To do so, A has to pay 12 ECU (from their exploration credit). One B-type participant is then randomly selected. This B's screen shows the same information as discussed above, but now for six different contracts (from three of the four companies). B here suggests three ranked contracts from the six to participant A. In addition to the potential bonus, B receives a fixed fee of 14 ECU (debited from A's initial wealth). A screenshot of the interaction with B as broker or tied-agent appears in Appendix A.

Note that the difference between tied-agents and brokers comes from the nature of their relationship with the insurance companies: brokers can sell insurance from different insurers, while tied-agents are constrained by an exclusivity contract to offer insurance from only one company.

Last, A can explore the market using a comparator, corresponding to a cyber-broker (also called an aggregator). Using the comparator costs 12 ECU (debited from the exploration credit). Six of the eight possible contracts then appear on A's screen (from three of the four companies). Only premium information is shown: to find out the associated deductible of a contract, A has to pay 3 ECU (i.e. it is possible to underwrite a contract without knowing the corresponding deductible). The comparator does not rank these contracts.

Figure 1



Subjects can continue to explore as long as they have exploration credit. We explain below how we define the search costs. To sum up, Figure 1 sets out the different decisions and potential interactions between players.

The final gain for this part of the experiment is that from one of the last six rounds, randomly selected (the first two rounds are trials). The loss event comes about according to the probability in this selected round. In addition to the potential gains from player interaction, B's receive a fixed endowment in this part.

2.3.2 Theoretical Framework

2.3.2.1 The definition of contracts

For each round, we generate eight different contracts, defined by a premium CP and a deductible D. The contracts are designed as in Schlesinger [2013] such that

$$CP = (1+\lambda)p \times R \times \alpha, \tag{1}$$

where λ is the loading factor of the insurer, p the probability of loss, R the amount of the loss and α the coverage rate. In order to offer contracts similar to those in the real world, we define a deductible D from (1) such that

$$\alpha = \frac{(R-D)}{R} \Leftrightarrow D = R - \frac{CP}{(1+\lambda) \times p}. \tag{2}$$

We generate for each round a set of contracts G_1 such that

$$\left\{ G_1 = CP_{G_1} \in [0, W]; D_{G_1} = R - \frac{CP_{G_1}}{(1+\lambda) \times p}, \lambda \in [-0.2, 1] \right\}. \tag{3}$$

For simplicity, we round each element to the nearest integer.

We then define a new subset $G_2 \subset G_1$ such that all contracts are unique, possible and non-dominated. We define a possible contract k such

$$W - CP_k - D_k - 14 > 0. \tag{4}$$

We cannot offer contracts that produce a negative final gain in a given period. As a reminder, 14 ECUs correspond to the fixed fee paid to B when A underwrites a contract via B's intermediation: this is the fee paid for broker advice.

A contract i is dominated by contract j if $CP_i > CP_j$ and $D_i > D_j$. We exclude dominated contracts as these could affect purchasing decisions and, in the real world, contracts include so many different elements that it is difficult to say that one contract clearly dominates another. We finally randomly draw eight contracts from G_2 in each period.

2.3.2.2 The definition of ranking

In order for intermediaries to provide advice in insurance markets, we give them private information via a ranking of contracts. Contracts are ranked by expected utility based on risk aversion. For simplicity, and because wealth changes from one round to another, we use a CRRA utility function (Constant Relative Risk Aversion). The use of IRRA or DRRA (Increasing/Decreasing relative risk aversion) (Saha [1993]) requires the estimation of two parameters, and therefore multiple applications of the Holt and Laury test with different levels of wealth. We therefore assume that consumers display the same risk-aversion for any risk-wealth ratio:

$$U(x) = \begin{cases} \frac{x^{1-r}}{1-r}, & \text{if } r \neq 1 \\ \ln(x), & \text{otherwise} \end{cases}, \tag{5}$$

where r is the aversion parameter with $r = 0$ for risk-neutral subjects, and $r > 0$ (resp. $r < 0$) for the risk-averse (resp. risk lovers). A contract i is optimal with respect to another contract j at round t if

$$p_t \times U(W_t - CP_{i,t} - D_{i,t}) + (1-p_t) \times U(W_t - CP_{i,t}) > p_t \times U(W_t - CP_{j,t} - D_{j,t}) + (1-p_t) \times U(W_t - CP_{j,t}). \tag{6}$$

The next step consists in the definition of the subject's risk-aversion parameter from the answers to the MPL (Multiple Price List). As risk aversion is different in the gain and loss domains (Tversky and Kahneman [1981]) and insurance consumers face risks in the loss domain, we use only the answers from the loss domain.

To do so, we take the mean of the Holt and Laury intervals (see Table 1), which gives us a coefficient according to the first switch from a safe to a risky option. It can be argued that our ranking definition is based on a strong hypothesis. As suggested in Kobberling and Wakker [2005], the reference point (here initial wealth) may play an important role in the risky decision. However, parameter estimation at the individual level would require multiple decisions for the same subject, which, for time reasons, is unrealistic in our experiment. Another criticism refers to our definition

Table 1 – Risk Aversion Parameters (Holt and Laury [2002])

Questions of first switch from Safe to Risky Option	Range of Relative Risk Aversion	Risk Preference Classification	Parameters Used
0-1	$r \leq -0.95$	highly risk loving	-0.95
2	$-0.95 < r < -0.49$	very risk loving	-0.72
3	$-0.49 < r < -0.15$	risk loving	-0.32
4	$-0.15 < r < 0.15$	risk neutral	0
5	$0.15 < r < 0.41$	slightly risk averse	0.28
6	$0.41 < r < 0.68$	risk averse	0.55
7	$0.68 < r < 0.97$	very risk averse	0.83
8	$0.97 < r < 1.37$	highly risk averse	1.17
9-10	$1.37 \leq r$	stay in bed	1.37

of risk aversion. A Fechner specification (popularized by Hey and Orme [1994]) or a Luce [1959] specification, which consists in the estimation of parameters by log-likelihood including all the answers to the MPL, could allow us to relax the hypothesis of expected utility. However, it also introduces assumptions about the distribution of the probability of choices. For a complete review of risk aversion in the laboratory, we refer to Harrison and Rutström [2008].

We do not suppose that we perfectly know participants' optimal policies. In reality, intermediaries provide advice with respect to their own knowledge and interpretation of the risk. Potential errors are therefore an integral part of the distribution process. In addition, the ranking does not much depend on risk aversion, with the margin defined as $\lambda \in [0.8, 2]$ playing a major role in the definition of optimality. Thus, rankings are almost the same for different levels of risk aversion. When a contract is optimal, it is so for about 30% of the risk-aversion profile defined as below. This reduces any problems of errors in ranking for individuals based on their risk aversion from the MPL.

2.3.2.3 The definition of search costs and the fixed fee

We include search costs defined as the cost of each exploration action. To encourage consumers to reveal their exploration preferences, in other words their distribution-channel preferences, we include a fixed search cost of x ECU to access each kind of exploration.

We add an additional search cost u for asking for a recommendation within a specific menu. This cost represents the time spent with a tied-agent in a traditional insurance context, as well as the time spent on the phone with an insurance advisor. We also add an additional search cost y for the revelation of deductible information by the comparator. In reality, price comparators display a ranking of contracts depending mainly on the premium: consumers have to click on a particular contract to find out the details, which is costly.

Last, consumers pay an additional fixed fee k to underwrite a contract that is suggested by the advisor. This cost represents the fees paid to a broker in exchange for their services. We do not consider this fee as a search cost, and it is therefore deducted from initial wealth.

These costs mentioned above are constrained in two ways. First, one channel should not dominate another. For instance, imagine that it is more expensive to seek out an advisor and underwrite through her than to consult four menus sequentially and ask for a recommendation for each of them. This will affect our results due to the presence of an optimal exploration strategy whatever the subjects' attributes and the round parameters.

We hence set search costs and the advisor fixed fee so that the expected costs of underwriting the optimal contract in the market are the same for each intermediary. We of course assume at this stage that there is no problem of obfuscation (the identification of optimal contracts) and beliefs about honesty. We thus define the expected matching cost (EMC) for each decision design as follows:

$$EMC(Advisor) = k + \frac{8}{6} \tag{7}$$

$$EMC(Comparator) = \frac{8}{6}(x + y + \frac{5}{6}y + \frac{4}{6}y + \frac{3}{6}y + \frac{2}{6}y + \frac{1}{6}y) \tag{8}$$

$$EMC(Menu) = x + \frac{3}{4}x + \frac{2}{4}x + \frac{1}{4}x \tag{9}$$

Using (7),(8) and (9), we have

$$EMC(Advisor) = EMC(Comparator) = EMC(Menu) \Leftrightarrow \tfrac{4}{3}x + k = 4x = \tfrac{4}{3}(x + 6y).$$

We in addition do not want to limit subjects in their exploration and let them explore the entire market. We assume that it is always possible to be fully informed but that consumers do not benefit from any time saved. Thus, $C = 7x + 6y + 4u$, where C is the exploration credit.

2.3.2.4 The definition of the bonus

As mentioned below, intermediaries are financially motivated by insurers in order to build up profitable portfolios. We thus introduce bonuses for each contract proposed. These bonuses represent the commission paid by insurers to their 'human' intermediaries (brokers or tied agents). In our game, we randomly define bonuses such that

$$B_i = \max((CP_i - p \times (R - D_i)) \times \mathcal{U}(0.2; 0.4), 0). \tag{10}$$

The bonus is therefore proportional to the profit generated by the contract. Nevertheless, the bonus rate is defined as a uniform random variable over the interval (0.2, 0.4). The reason for doing so is that the most profitable contract should not be the most incentivized: insurers may wish to incentivize less-profitable contracts for reasons such as loyalty goals or brand image. We do however assume that non-profitable contracts are never incentivized.

3 Procedure

A web interface and server database were designed specifically for this experiment. The interface was developed with HTML and JavaScript, the backend with Java and PostgreSQL as the database. The subjects were students from the University of Lyon 1 – Claude Bernard, France. 217 subjects participated in the experiment, 27 in average for each session including 5 participants of type B.

The honesty game was played first. All subjects received identical instructions, including the comprehension questions. Subjects were assigned to a group for the rest of the session. Then, they made their decisions for this part. Afterwards, subjects received written instructions for the risk-elicitation task and made their choices. Finally, they received instructions for the main part of the experiment and a comprehension questionnaire that we corrected with them. Before leaving the room to privately receive their payments, we asked them to answer some general questions about age, gender and education. The different periods of the exploration game were displayed randomly for each session. All treatments were framed in a neutral manner.

We decided to play the honesty game at the beginning of the session to avoid learning effects from potential interactions during the main part of the experiment. The risk-elicitation task was played just before the main game in order to be able to rank contracts for each A subject. The payoffs in the different tasks were revealed at the end of the entire experiment. The sessions lasted about 105 minutes. The average payoff was about 16 Euros including a show up fee of 3 Euros.

For full transparency, we will make available the R code (RCore-Team [2018]) and experimental data used in this paper upon request. Please note that authors should be referenced in the case of the use of these data or this code for further research.

4 Results and Analysis

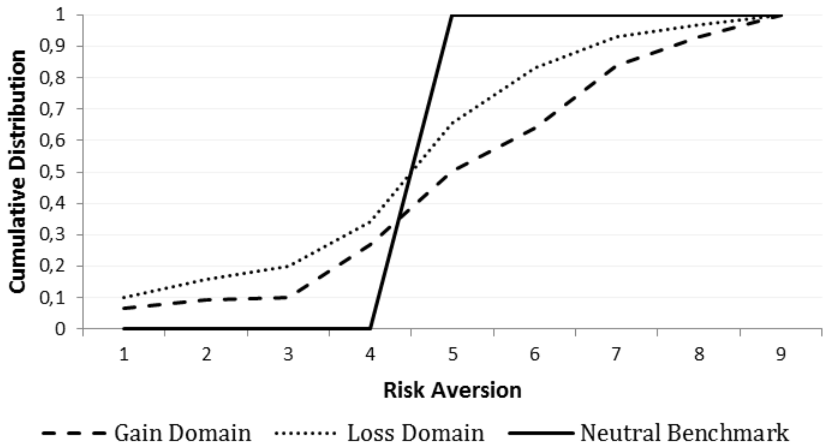
4.1 Subject variables: distribution and impact on the main game

4.1.1 Risk Aversion

We first construct, for each individual, two variables representing their risk aversion level in the gain and loss domain resulting from the Holt and Laury [2002] elicitation game. We look at risk aversion in both domains for two reasons. In insurance, there is a probability of wealth loss. However, while searching information, individuals are uncertain about the value of the information gain.

Risk aversion is defined by the number of the question of the first switch from the safe to the risky option. Neutral subjects will switch at question 5, while the risk-averse will switch later. The average question switch number is 5.56 in the gain domain and 4.82 in the loss domain. These figures are significantly different using a non-parametric two-sided Wilcoxon test ($p-value < 1.7e^{-6}$). This result is in line with Chakravarty and Roy [2009], who found significantly less risk-aversion in the loss than in the gain domain (Figure 2).

Figure 2 – Empirical cumulative distribution functions from 1st switch



We find that risk-averse individuals avoid search on their own, and prefer to compare offers via a cyber-broker or broker (Table 2). Risk aversion in the loss domain has a more significant impact than that in the gain domain for distribution-channel choice. The risk averse in the gain domain also collect more information in the exploration process (Table 5). However, contrary to standard expected-utility theory, neither risk aversion in the loss or gain domains affect contract choice (Table 6). Regarding intermediaries, we find a strong correlation between risk aversion in the loss domain and deviation behaviors (i.e. the suggestion of a non-optimal contract) (Table 9). Deviation is therefore considered to be a risky decision.

4.1.2 Honesty and beliefs about others' honesty

As we here analyze distribution-channel choice in insurance including human intermediaries, our second key variable is honesty. Honesty beliefs are individual, but we only observe actual honesty at the session level.

As a reminder, we distributed different draws to the five B participants in each session including 3, 4, 5, 6 or 7 red balls. We find interesting patterns of honesty and beliefs about others' honesty in the different draws (Mouminoux and Rulliere [2018]). The favorable draw produces more honesty and greater honesty expectations, as in Houser et al. [2012] and Galeotti et al. [2017]. For simplicity we here only use the answer of A faced with the least-fortunate draw given to the B's in each session (the draw with 7 red balls, where B should leave 3.5€ in the wallet according to the rule). This draw corresponds to the situation where honesty and beliefs about honesty are the most heterogeneous and the lowest. Honesty beliefs for subject i (i.e. HB_i) are defined as follows:

$$HB_i = answer_i - 3.5€ .$$

On average, A's think that B's will take 1.23€ more than the rule. Over the 177 A subjects, 41 trust the B's, 8 are over trusting (they think that the B's take less than the rule) and 128 are untrusting (they think that B's take more than allowed by the rule).

We define dishonesty at the session level as the average amount taken above the rule by the five B participants in each session. On average, the B's take 0.97€ more than the rule: 47% respect the rule and 35% fully deviate.

As risk aversion and honesty beliefs will be introduced together, we check the correlation between them: this is insignificant (Kendall, Pearson and Spearman correlation tests), as in the seminal paper of Eckel and Wilson [2004] who find no correlation between trust (in our case honesty beliefs) and risk aversion.

Honesty beliefs help explain insurance purchase. Those with high honesty expectations avoid cyber-brokers (Table 2) and are more sensitive to broker deviation, suggesting disappointment (Table 4). They are also less affected by the anchoring effect in their contract choice (Table 7). Regarding intermediary behavior, we find a correlation between honesty and the deviation rate at the session level. The more honest B players are less likely they deviate in their suggestions (Table 9).

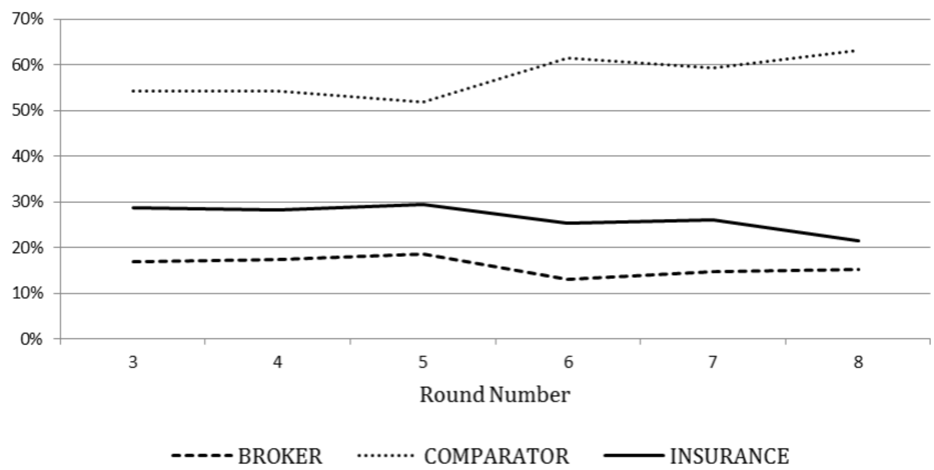
4.2 Purchasing Process

As noted above, we break the purchasing process down into two parts: subjects explore the market to uncover alternatives before choosing an insurance contract. We are first interested in the 'search strategy', i.e. the determinants of distribution-channel choices. We then investigate extreme search strategies: subjects who adopt a 'saving search cost strategy' (i.e. take the lowest price on the comparator without uncovering the deductible) and the 'deep search cost strategy' (i.e. subjects who uncover at least one contract from all insurers). Then, given the information from these search strategies, we consider the final insurance contract choice.

4.2.1 Search Strategies

Figure 3 shows final channel decision of type A individuals. Globally over the entire experiment, we note that 57.4% (std. dev. 0.045) of subjects chose their insurance via the comparator, while 16.0% (std. dev.0.029) chose via a broker and 26.6% (std. dev.0.029) directly from an insurer. However, from Figure 3, we see that channel choice changes over round, with a rise in the use of comparators over time. We first focus on first channel choices and inter-period learning effects. We then investigate the final underwriting choices and intra-period channel decisions.

Figure 3 – Percentage of CHoices by Underwritting Distribution Channel



4.2.1.1 First Channel Choices and inter-period effects

In the following, we consider a series of three statistical models to analyze first channel choices and inter-period effects, where the reference level is the broker channel. We first carry out a multinomial logistic regression including random effects (Table 2, Model 1) with the first channel choices as the dependent variable (i.e. Broker, Comparator or Insurer). Random effects allow us to control for the relationship between errors in our panel data (see e.g. Croissant [2013]). In the first two regressions, we consider only non-lagged explanatory variables.

Honesty beliefs are a significant determinant of first channel choices. The probability that subjects first choose the comparator falls with honesty beliefs ($p - value < 0.001$). Conversely, the probability of first choosing a particular insurer rises with honesty beliefs ($p - value < 0.1$). However, risk averse individuals avoid insurance as a first choice ($p - value < 0.001$). Regarding the 'round number' coefficient, only the probability of loss has a significant effect on first choices: a higher probability leads subjects to first turn to a broker for advice ($p - value < 0.001$).

Model 2 of Table 2 demonstrates learning effects in the significance of the round number. However, the previous results on honesty beliefs, risk aversion and probability of loss continue to hold.

Finally, by incorporating dummies of lagged variable, we try to explain this learning effect in Model 3 of Table 2, where we add the subject's previous round's first choice to capture hysteresis in choice. Only subjects who choose self-search demonstrate persistence (the coefficient on 'First Choice t-1 Insurance X Insurance' = 1.20, $p - value < 0.05$). We also add a dummy variable for the subject having asked for advice (though a broker or insurer) in the previous period and having received sub-optimal advice. We find no effect here: subjects do not seem to detect or to take into account deviation in previous rounds.

While the choice of the comparator as the first exploration channel rises over time, this probability significantly falls with the number of revealed contracts in the previous period ($p - value < 0.05$).

Table 2 – Multinomial Logistic Regression including Random Effect

Explanatory Variable	**Rounds' First Choice Channel**					
	Model 1		**Model 2**		**Model 3**	
Coefficients *Std. error*	COMPARATOR	INSURANCE	COMPARATOR	INSURANCE	COMPARATOR	INSURANCE
Honesty Belief Level	−0.67*** *0.12*	0.26* *0.14*	−0.69*** *0.12*	0.29** *1.99*	−0.79*** *0.16*	0.24 *0.17*
Risk Aversion	−0.01 *0.07*	−0.40*** *0.09*	0.00 *0.07*	−0.41*** *0.09*	0.04 *0.08*	−0.35*** *0.11*
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*		
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*		
Probability of Loss	−4.42*** *1.29*	−3.44*** *1.63*	−4.32*** *1.30*	−3.67*** *1.65*	−3.78*** *1.04*	−3.03*** *1.30*
Round number			0.14* *0.07*	−0.22** *0.10*	0.23** *0.11*	−0.26** *0.26*
First choice $t-1$: COMPARATOR					−0.23 *0.46*	0.60 *0.58*
First choice $t-1$: INSURANCE					0.47 *0.47*	1.20** *0.60*
Deviation $t-1$					−0.08 *0.42*	0.31 *0.53*
Contract nb. discovered $t-1$					−0.18** *0.08*	−0.06 *0.10*
Constant (ref. level: BROKER)	2.07*** *0.53*	2.24*** *0.65*	1.25* *0.67*	3.44*** *0.81*	1.08 *0.98*	2.70** *1.08*
Nb. Observations	1062		1062		865	
Nb. Subjects	177		177		177	
R^2	0.336		0.346		0.340	
Adjusted R^2	0.327		0.336		0.325	

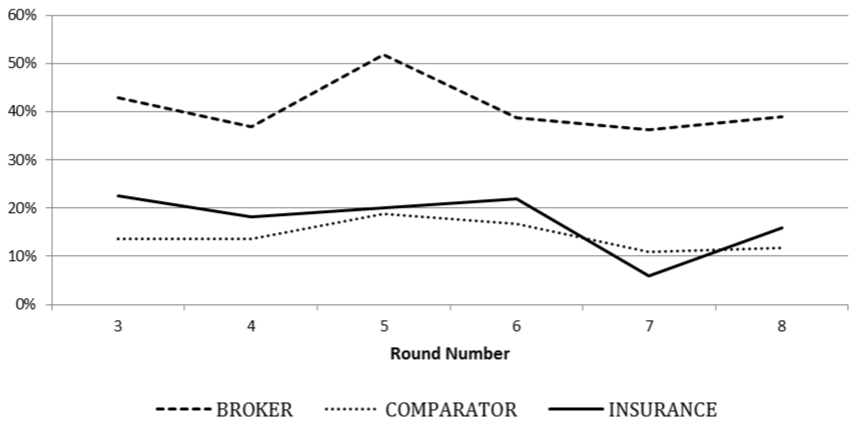
Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

This learning effect may reflect obfuscation: when subjects are faced with too much information they may realize that the analysis is complicated and favor channels with human intermediaries. The other estimated coefficients in Model 3 are similar to those in Models 1 & 2.

4.2.1.2 Intra-Period switching behavior

Now, we consider a series of four statistical models to analyze intra-period switching behavior, still with the reference level being the broker channel. Over the entire experiment, we note that 21.0% (std. dev. 0.047) of subjects decide to switch channel type at least once during a round. Figure 4 shows the percentage of switches with respect to the first channel choice. On average, 41.7% (std. dev. 0.058) of subjects who first chose a Broker switch, with the analogous figures for Comparator and Insurance being 14.1% (std. dev. 0.030) and 17.6% (std. dev. 0.061). Among the switchers, 15.2% (std. dev. 0.032) finally return to their first choice.

Figure 4 – Percentage of Switch by First Choice Channel



In Model 4 of Table 3, we show that these switches are not explained by the round parameters or subject variables. Only first channel choice in the period is significant ($p - value < 0.001$) in explaining the final underwriting channel choice.

Table 3 – Multinomial Logistic Regression including Random Effect

Explanatory Variable	**Rounds' Underwriter Channel**	
	Model 4	
Coefficients *Std. error*	Comparator	Insurance
Honesty Belief Level	0.00 *0.15*	0.06 *0.15*
Risk Aversion (loss)	0.10 *0.09*	0.06 *0.09*
Initial Wealth	0.00 *0.00*	0.00 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*
Probability of Loss	−0.19 *1.58*	−1.35 *1.58*
Round number	0.08 *0.09*	0.04 *0.10*
First choice $t-1$: Comparator	5.50*** *0.42*	2.44*** *0.43*
First choice $t-1$: Insurance	2.44*** *0.54*	5.45*** *0.49*
Constant (ref. level: Broker)	−2.62*** *0.94*	−2.92*** *0.90*
Nb. Observations	1062	
Nb. Subjects	177	
R^2	0.505	
Adjusted R^2	0.495	

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

We find intra-period inertia in choice and, when subjects switch, they prefer to switch between the comparator and an insurer. Switching might depend on first channel choice and we do not capture this effect in Model 4. We thus separate our sample into three parts conditional on first channel choice, and run for each a logistic regression where the dependent variable is a dummy for the subject switching channel type during the round (Models 5, 6 and 7 of Table 4).

Model 5 focuses the switching analysis on subjects who first chose a Broker. The round parameters and risk aversion do not affect switching. We then consider the deviation degree, defined as the average gap between the ranks of the three contracts proposed compared to the optimal ranking that appears on the brokers' screen. This deviation degree is computed for each interaction between A and B. If the broker proposes the ranking that appears on the screen, then the deviation degree is zero.The maximum deviation degree would come from proposing the worst contract (ranked 6) first, then the second worst (ranked 5) second, and the third-worst third: this produces an average gap of $\frac{1}{3}((6-1)+(5-2)+(4-3)) = 3$. The probability of switching rises with deviation degree, in particular for subjects with high honesty expectations.

Contrary to the lack of an inter-period deviation learning effect (Model 3 of Table 2), subjects do take into account intra-period deviation. They react more strongly when they are disappointed by their choices. We also control in Model 5bis of Table 4 bis in Appendix B where the subjects switch to. The results are in line with our intuition: disappointed subjects choose the comparator channel which does not include 'human' intermediaries.

The results are different for subjects who first choose insurers (Model 6 of Table 4) here only honesty beliefs significantly predict switching and switchers tend to change to the comparator (Model 6bis of Table 4 bis bis in Appendix B). Deviation by tied-agents does not affect switching. However, we prefer to avoid any misinterpretation of these results due to a lack of power: recommendations for only one insurer by a tied agent were only requested 10 times.

Table 4 – Logistic Regression including Random Effect

Explanatory Variable	**Rounds' Underwriter Channel**		
	Model 5	**Model 6**	**Model 7**
Coefficients	BROKER	INSURANCE	COMPARATOR
Std. error			
Honesty Belief Level	−0.98	0.74**	0.39*
	0.80	*0.37*	*0.23*
Risk Aversion (loss)	−0.06	−0.06	−0.04
	0.18	*0.19*	*0.13*
Initial Wealth	0.00	0.01	0.00
	0.00	*0.01*	*0.00*
Loss Amount	0.00	0.00	0.00
	0.00	*0.00*	*0.00*
Probability of Loss	3.96	−2.15	4.32
	2.81	*3.26*	*2.14*
Round number	−0.18	−0.18	−0.20
	0.17	*0.23*	*0.15*
Deviation Degree	0.59**	0.53	
	0.30	*0.45*	
Deviation Deg. x Honesty Belief	0.58**	−0.19	
	0.24	*0.33*	
Constant	−2.19	−3.73**	−2.01
	1.75	*1.86*	*1.38*
Nb. Observations	237	210	615
Nb. Subjects	79	67	140
R^2	0.272	0.167	0.177
Adjusted R^2	0.239	0.126	0.164

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

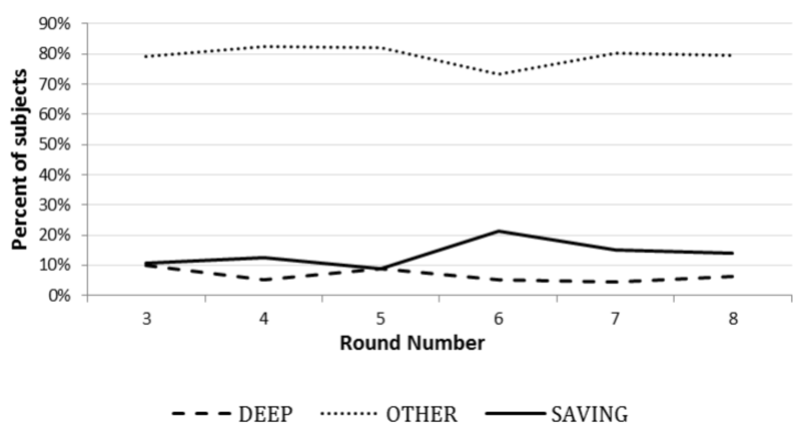
Finally, Model 7 of Table 4 focuses on subjects who first choose the comparator. We here include the number of deductible values uncovered. As expected, switch probability falls with the latter: revealing the deductible value is costly. We also test for linearity here, and find that when the number of deductibles is large enough, the probability of switch increases (i.e. the coefficient on the squared term is positive).

In Model 7bis of Table 4 bis in Appendix B, we find that these effects are significant only for those who switch from the comparator to an insurer. Only 15 subjects switch from the comparator to brokers. This lack of observations prevents us from modelling this specific switch. However, all of the previous results continue to hold for switchers from comparator to insurers. The positive effect of the deductible on switches from the comparator to insurers can be explained by some subjects deciding to adopt a “deep search strategy”, by obtaining information on at least one contract from each insurer. As a reminder, the comparator offers information for three of the four insurers in the market. By first using the comparator and revealing at least 4 deductibles, subjects can then obtain complete information about at least one contract from all three of these insurers. They can then select the missing insurer and collect information about at least one contract for all insurers on the market. This leads us to analyze extreme search strategies.

4.2.1.3 ‘Saving Search’ and ‘Deep Search’ strategies

We here focus on extreme search strategies. We split our observations up into three different profiles (Figure 5). We identify two extreme strategies corresponding to extended and restrained search, as opposed to various moderate search strategies. 6.7% of subjects obtain information about at least one contract from all insurers: we call this the ‘deep search strategy’. On the contrary, 13.8% of subjects choose ‘saving search’, selecting the comparator as first channel choice and underwriting the contract with the lowest premium. Strategy choice is not affected by round number, meaning there are no learning or boredom effects.

Figure 5 – Distribution of Search Profile by Round Number



We carry out multinomial logistic regressions to investigate extreme search strategies. We find in Models 8 and 9 of Table 5 that the probability of loss has a significant impact. As this probability rises (falls), the probability of choosing a saving (deep) search strategy rises. In other words, subjects prefer to explore the market as the probability of losing part of their wealth rises. We in addition see that subjects who believe in others’ honesty avoid the saving search strategy ($p-value < 0.001$). For the same search cost, these subjects could obtain more information by choosing a broker but could then be confronted with deviation.

Table 5 – Multinomial Logistic Regression including Random Effect

Explanatory Variable	Rounds' First Choice Channel					
	Model 8		Model 9		Model 10	
Coefficients *Std. error*	Saving	Deep	Saving	Deep	Saving	Deep
Honesty Belief Level	-0.46^{***} *0.11*	0.10 *0.17*	-0.50^{***} *0.11*	0.16 *0.17*	-0.49^{***} *0.11*	0.18 *0.17*
Risk Aversion (gain)			-0.22^{**} *0.07*	-0.11 *0.10*	-0.22^{**} *0.07*	-0.11 *0.10*
Risk Aversion (loss)	-0.07 *0.07*	-0.06 *0.10*				
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*		
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*		
Probability of Loss	-4.50^{***} *1.32*	3.67^{**} *1.79*	-4.52^{***} *1.31*	3.58^{**} *1.80*	-3.35^{***} *0.93*	3.34^{**} *1.22*
Round number					0.12 *0.08*	-0.18 *0.11*
Constant (ref. level: Others)	-2.14^{**} *0.66*	-4.85^{***} *0.94*	-1.30^{**} *0.66*	-4.39^{***} *0.96*	-1.73^{***} *0.65*	-3.02^{*} *0.89*
Nb. Observations	1062		1062		865	
Nb. Subjects	177		177		177	
R^2	0.176		0.183		0.184	
Adjusted R^2	0.163		0.172		0.174	

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

Unlike to our other models, risk aversion is only significant in the gain domain here ($p-value < 0.001$). As noted above, information search introduces uncertainty about the value of the information gain. We can thus argue that risk-averse subjects prefer to reveal more in order to reduce this uncertainty. However, we find no significant differences between the standard and deep extreme strategies by risk aversion. Finally, we control in Model 10 of Table 5 for any learning or boredom effects by adding the round number. This does not attract a significant coefficient and the other results are unaffected.

4.2.2 Contract Choice

After determining the search strategy of subjects, we now focus our analyses on the final contract choices. We first determine drivers of coverage choices and highlight some focal point and anchoring effects. We finally investigate consequences of quantity of information on efficiency of choices with respect to the Expected Utility Theory.

4.2.2.1 Coverage choice

This subsection focuses on subject contract choices. We first estimate the relative coverage chosen via a linear regression. As a reminder, coverage α is defined as follows $\alpha = \frac{LossAmount-Deductible}{LossAmount}$. We here model relative coverage to standardize the dependent variable across subjects, as they do not face the same choice set, defined as $\frac{Coverage-Min.\ coverage\ available}{Max.\ coverage\ available-Min.\ coverage\ available}$.

Relative coverage is 0 if the subject choses the minimal coverage available and 1 if she chooses the maximum coverage. The regressions cover subjects who have at least two choice possibilities:

we saw above that some subjects adopt a 'saving search strategy' so that they do not compare contracts.

As expected, coverage rises with the probability of loss ($p - value < 0.001$ in Models 11, 12 and 13 of Table 6), but falls with the number of alternatives (Model 12, Table 6). As the coverage choice and the number of alternatives are both linked with the search strategy, we control for this in Model 13. We find no significant effect of the latter, and the number of alternatives remains positive and significant.

This result leads us to investigate in more detail the effect of available information on contract choice. Contrary to what might have been expected, contract choice is not mainly driven by standard parameters (except for the probability of loss) but more by the information available. We suspect a focal-point effect due to obfuscation here: subjects with too much information end up making their choices based only on the simplest characteristic: the premium. As we designed the experiment to avoid strictly-dominated alternatives, the lowest coverage here corresponds to the lowest premium.

Table 6 – OLS Regression including Random Effect

Explanatory Variable	**Relative Coverage Choice**		
Coefficients *Std. error*	**Model 11**	**Model 12**	**Model 13**
Honesty Belief Level	0.02 *0.02*	0.02 *0.02*	0.02 *0.02*
Risk Aversion (loss)	0.00 *0.01*	0.00 *0.01*	0.00 *0.01*
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Probability of Loss	0.33** *0.15*	0.36** *0.15*	0.35* *0.15*
Round number	0.00 *0.01*		
Nb available alternative		−0.02** *0.01*	−0.02* *0.01*
First choice t: COMPARATOR			−0.01 *0.05*
First choice t: INSURANCE			0.06 *0.04*
Constant	0.36*** *0.09*	0.41*** *0.08*	0.43*** *0.08*
Nb. Observations	915	915	915
Nb. Subjects	171	171	171
R^2	0.021	0.025	0.028
Adjusted R^2	0.014	0.019	0.020

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

4.2.2.2 Focal-point and Anchoring effects on contract choice

In order to control for focal-point effects regarding the premium, we run a logistic regression on a dummy indicating individuals choosing the lowest price. With more alternatives, the probability of choosing the lowest price should fall. However, Models 14, 15 and 16 of Table 7 show that the more alternatives subjects have the more likely they are to choose the lowest price. This is consistent with focal points.

Contrary to previous models of coverage choice, we find that the probability of loss increases the probability of choosing the best price. This point encourages us to control for eventual anchoring effects. By construction, the higher the probability of loss the higher the premium, in a given round. We could then argue that the probability of choosing the lowest price rises with the price, independently of the probability of loss.

To avoid the misinterpretation of this coefficient we add in Model 15 (7) the difference between the average and minimal premium. We find a significant anchoring effect, and the probability of loss is no longer significant. In other words, adding a coefficient for the difference between the average and the minimal premium reduces significantly the probability of choosing the lowest price.

Table 7 – Logistic Regression including Random Effect

Explanatory Variable	**Lowest Price**		
Coefficients *Std. error*	**Model 14**	**Model 15**	**Model 16**
Honesty Belief Level	0.13** *0.06*	0.14** *0.07*	0.13** *0.07*
Risk Aversion (loss)	−0.02 *0.04*	−0.03 *0.04*	−0.04 *0.04*
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Probability of Loss	2.79*** *0.76*	0.45 *0.98*	0.35 *0.98*
Round number	−0.01 *0.04*	0.00 *0.05*	0.00 *0.05*
Nb available alternative	0.31*** *0.05*	0.49*** *0.06*	0.49*** *0.06*
Average Premium - Minimal Premium		−0.02*** *0.00*	0.02*** *0.00*
First choice t: COMPARATOR			−0.21 *0.19*
First choice t: INSURANCE			−0.31 *0.24*
Constant (ref. level: NO)	−0.77* *0.09*	−0.70 *0.08*	−0.48 *0.08*
Nb. Observations	1067	1067	1067
Nb. Subjects	177	177	177
R^2	0.068	0.095	0.097
Adjusted R^2	0.060	0.086	0.087

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

To sum up, subjects with 'too much' information make their decisions based on the premium: this is the focal-point effect due to obfuscation. However, their decisions are also driven by all available contract information, and as the average premium rises relative to the minimum, the probability of choosing the cheapest contract falls: this is the anchoring effect. We could argue that consumers facing large price differences between the cheapest contract and the others may interpret this as a negative 'quality' signal. This is related to honesty beliefs significantly increasing ($p - value < 0.05$) the probability of choosing the lowest premium (Models 14, 15 & 16), as if subjects who believe in honesty are unaffected by this negative signal effect.

4.2.2.3 Efficiency of Choices

In this section, we focus our analysis on the efficiency of choices of subjects. As detailed previously, the 8 available contracts are ranked according to the Expected Utility Theory. In average , 44% (std. dev. 0.04) of subjects choose the optimal contract through the discovered contracts (i.e. available alternative at the choice moment). Hence, a majority of subjects does not make their choices according to the standard Expected Utility Theory. As previously seen, the quantity and quality of information are significant drivers on final contract choices.

We thus perform models in order to determine the role of obfuscation (i.e. quantity of information) and intermediaries' honesty (i.e. quality of information) on the efficiency of choices. In Model 17, 18, 19 of Table 8, the dependent variable is a dummy for the subject choosing the optimal contract according to the Expected Utility Theory. We perform our models on only subjects having complete information about at least two choices and underwriting a contract with complete information. We consider 892 observations over the 1062 collected (i.e 84%). Indeed, some subjects discover more than two contracts but finally decide to select a contract without knowing its relative information. Hence, she is not able to determine the rank of this contract with respect to others contracts discovered.

We firstly model the probability to choose the optimal contract with respect to the rounds' parameters (i.e. probability of loss, loss amount and initial wealth), subject variables (honesty belief level and risk aversion level) and the number of available alternative (Model 17, Table 8). We find that round parameters and subject variables are not significant to explain non-efficient choices.

However, when the number of alternative rises, the probability to make an inefficient choice significantly increases. While one could argues that most informed consumers should make more efficient choices, we show that too much choices lead to inefficient decision. Because distribution channels do not imply same level of obfuscation or honesty, we add in Models 18-20 (Table 8) a coefficient either for the interaction between the number of alternative and the channel choice or for the interaction between the deviation and the channel choice. In Model 18, we find that obfuscation is a significant source of inefficient decision only for subjects underwriting through comparator. The number of alternative increases the probability of inefficient choice in particular when consumers do not decide to ask or follow advices. This result supports our first intuition of limited discernment of subject due to obfuscation.

While obfuscation is particularly present for comparator, others' channels including physical intermediaries could also conduct to inefficiency since quality of information implies honesty of intermediaries. However, intermediaries have their own financial incentive, leading to deviation (i.e. deviation is represented here as a dummy for the intermediaries who do not advice the optimal contract at first). We find in Model 19 of Table 8 that deviation of intermediaries significantly increases the probability of inefficient choices. In other words, subject avoiding obfuscation by delegating a part of their decision to a physical intermediaries are also expose to inefficiency on decision-making. Interestingly, by adding an interaction variable between deviations and underwriting channel choice we also show that consumers having faced deviation and finally choosing comparator make more optimal choices. We can expect that consumers detecting deviation and deciding to switch channel get the highest ability to detect the most efficient contract.

Last, we include in Model 20 of Table 8 two dummies for subjects choosing the lowest price, both for single and cross effects. Indeed, we show in Table 7 of the previous section that obfuscation lead to focal point effect. While choosing the lowest price tends to increase the probability of optimal choices, we find that when this choice is made because of focal point effect due to obfuscation the efficiency of choices decreases. We also control in all previous models eventual leaning effect thanks to the round number variable and do not find any.

Table 8 – Logistic Regression including Random Effect

Explanatory Variable	**Optimal Choice (EUT)**			
Coefficients *Std. error*	**Model 17**	**Model 18**	**Model 19**	**Model 20**
Honesty Belief Level	0.07 *0.06*	0.32 *0.67*	0.06 *0.07*	0.08 *0.07*
Risk Aversion (loss)	0.06 *0.04*	0.07 *0.04*	0.08 *0.04*	0.07 *0.04*
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Probability of Loss	−0.90 *0.75*	−0.57 *0.78*	−1.09 *0.76*	−0.57 *0.78*
Nb available alternative	−0.37*** *0.05*	−0.03 *0.17*	−0.12 *0.16*	−0.03 *0.17*
Underwriting Channel t: COMPARATOR		−0.08 *0.70*	0.17 *0.68*	−0.08 *0.70*
Underwriting Channel t: INSURANCE		−0.25 *0.71*	0.06 *0.69*	−0.25 *0.71*
Deviation			−0.98** *0.37*	−0.88** *0.39*
Lowest Price				2.11*** *0.43*
Underwriting Channel t: COMPARATOR x Nb available alternative		−0.30* *0.17*	−0.35* *0.18*	−0.30* *0.18*
Underwriting Channel t: INSURANCE x Nb available alternative		−0.21 *0.16*	−0.23 *0.17*	−0.19 *0.18*
Underwriting Channel t: COMPARATOR x Deviation			1.83** *0.57*	1.59** *0.59*
Underwriting Channel t: INSURANCE x Deviation			0.33 *0.56*	0.23 *0.62*
Lowest Price x Nb available alternative				−0.23** *0.11*
Round Number	0.03 *0.04*	0.03 *0.04*	0.03 *0.05*	0.02 *0.05*
Constant (ref. level: NO)	0.89** *0.44*	0.32 *0.67*	0.83 *0.75*	0.08 *0.78*
Nb. Observations	892	892	892	892
Nb. Subjects	171	171	171	171
R^2	0.065	0.069	0.081	0.129
Adjusted R^2	0.055	0.056	0.064	0.111

Signif. codes for p-values: 0 ‘***’ 0.001 ‘**’ 0.05 ‘*’ 0.1 ‘ ’ 1

4.3 Intermediary strategies

We last examine the behavior of subjects playing ‘human’ intermediaries (the B’s). On average, each B subject is called 1.2 times per round. The B-type players have financial incentives via the bonuses: just over 60% of the time they do not propose the best policy to subjects who ask for advice. We run a logistic regression on a dummy indicating for intermediary deviation (not first suggesting the best contract).

The consumer variables (initial wealth, the loss amount and the probability of loss) do not affect deviation (Models 21, 22 and 23 of Table 9). However, risk-averse intermediaries deviate less ($p - value < 0.05$). As a reminder, they receive the contract bonus only if the customers choose the policy via their intermediation. Deviation is hence considered as a risky decision.

Moreover, and as expected, deviation falls with the bonus of the optimal contract (Model 21). However, the difference between the average possible bonus and the optimal-contract bonus is more significant in explaining deviation: a smaller gap here produces less deviation.

We also control for intermediary type and find that when the demand for advice comes from a particular insurer (versus a broker) intermediaries deviate significantly less ($p - value < 0.05$). The reason is simple: participants only receive two different contracts from insurers but six from brokers.

We consider honesty at the session level from the honesty game and the intermediary deviation. After controlling for session effects (Model 21 bis of Table 9 bis in Appendix B), we find a strong correlation between deviation in the honesty game (called 'Dishonesty Session Level' here) and intermediary deviation. This result comforts or idea about the existence of close relationship between deontological ethics imposed to insurance physical intermediaries and honesty concept.

Finally, we look for portfolio effects by adding the number of demands previously received during the round. If deviation is risky, intermediaries receiving a number of demands for advice in the same round may diversify their risks. However, we do not find any significant evidence of this.

Table 9 – Logistic Regression including Random Effect

Explanatory Variable	**Deviation**		
Coefficients *Std. error*	**Model 21**	**Model 22**	**Model 23**
Risk Aversion (loss)	-0.28^{**} *0.09*	-0.28^{**} *0.09*	-0.28^{**} *0.09*
Initial Wealth	0.01 *0.00*	0.00 *0.00*	0.00 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*
Probability of Loss	-2.22 *1.66*	-0.67 *1.68*	-0.53 *1.71*
Optimal Contract Bonus	-0.05^{*} *0.02*	0.06 *0.04*	0.06 *0.04*
Status: TIED-AGENT	-1.28^{*} *0.68*	-1.47^{**} *0.64*	-1.46^{**} *0.64*
Dishonesty Session Level	0.59^{**} *0.26*	0.63^{**} *0.26*	0.62^{**} *0.26*
Round Number	-0.01 *0.10*	0.00 *0.10*	0.00 *0.10*
Mean Bonus - Optimal Contract Bonus		0.18^{**} *0.06*	0.18^{**} *0.06*
Nb of demand received			0.10 *0.32*
Constant (ref. level: NO)	2.66^{**} *0.89*	3.09^{**} *0.98*	2.88^{**} *1.07*
Nb. Observations	289	289	289
Nb. Subjects	40	40	40
R^2	0.181	0.213	0.210
Adjusted R^2	0.152	0.182	0.176

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

5 Conclusion

In this paper, we analyze the purchasing behavior in personal non-life insurance markets. The personal insurance market is a useful context in which to analyze purchasing behavior, as it includes a number of types of intermediaries. Consumers can explore the insurance market via brokers, cyber-brokers or directly visit a specific insurer and may ask tied-agents for advice. Based on the search-cost theory, we here designed an experiment to help understand distribution-channel choices. The complexity of insurance supply, including different levels of coverage, premium and deductibles gives room for obfuscation, which appears to be a marketing device and source of inefficiency in decision-making.

Consumers can decide to explore the market on their own, but have to deal with many comparisons involving incomplete information. Another possibility is then to ask for advice to help choose. Although the deontological rule implies that intermediaries should provide the best advice, they are themselves influenced by incentives such as bonuses or lobbying. We find that this kind of delegation is conditional on honesty beliefs.

Even with considerable intermediary deviation, the complexity of choices in a risky environment and obfuscation drive subjects to delegate part of their decisions. Even with free access to online insurance markets, our results suggest that consumers continue to value broker and tied-agent services although deviation leads to inefficient choices. However, deviation also explain dynamic of channel choices and consumers detecting deviation tends to switch channel and make more efficient contract choices.

We also find that intermediary behaviors depend on their risk aversion and the general honesty level, so that deviation is a risky decision. We present evidence of the importance of honesty and beliefs about others' honesty. Because both search strategy (i.e. delegation and self-exploration) are sources of inefficiency on decision-making, the development of multi-channel distribution strategy of insurers is essential to cover a large part of market. Some consumers have enough beliefs about others' honesty to delegate a part of their decisions and to avoid obfuscation.

However, the evaluation of the economic benefits of physical intermediaries remains difficult. While intermediary costs are easy to evaluate (the fees and bonuses), the associated benefit is not. On the one hand, consumers save on search costs and avoid obfuscation, but on the other these savings do not necessarily compensate for the risk of dishonesty. As in Bergstresser et al. [2009] we find that financial incentives for physical intermediaries produce sub-optimal contracts. Higher incentives push intermediaries to be more aggressive and makes them less honest. There is a potential crowding out effect of incentive towards consumers. In the context of multiple distribution channels, the design of physical intermediary incentives could lead to consumer mobility across channels.

In addition, we show that the quantity and quality of information have a considerable impact on final contract choice. While standard economic theory suggests that the main drivers are consumer risk-aversion and the nature of the risk, final choices in our experiment are based on the premium and the probability of loss. Anchoring effects regarding both of these, consistent with obfuscation, can lead to more price competition as insurance companies compete on the premium level.

We here look at compulsory insurance; we may expect some behavioral differences under optional insurance, in particular regarding selection. The risk-averse are more likely to purchase optional insurance (Corcos et al. [2017]). Also, as in Kuksov and Villas-Boas [2010], we can imagine that the effect of the number of alternatives under optional insurance might diminish the focal and anchoring effects, as consumers can decide against purchase.

In order to be able to compare the different distribution channels ceteris paribus, the proposed contracts are the same in each channel. However, real-world insurers do manage the policies that they propose according to the way in which they are distributed. For instance, due to the focal-point effect we can imagine that loss-leaders will appear on the comparator and that insurers will focus their efforts on cross-selling and upgrade options. This is particularly true when we take consumer search costs into consideration Diamond [1971]. In addition, brokers are likely better informed about the range of contracts that are available, and may propose contracts that are more difficult to find.

Our paper has focused on first insurance purchase: we have not looked at renewal and customer inertia due to switching costs. It would be of interest to adapt this experiment to a repeated game including renewal and switching costs, as in Schram and Sonnemans [2011], as well as retaining the possibility that consumers explore the market via the different channels.

Last, we uncover evidence of a correlation between customer risk profiles and their acquisition strategy. Risk aversion and honesty both reflect the individual risk profile. The first could explain adverse selection while the second could be related to fraud. The consumer's distribution-channel strategy could then reflect screening. We would now like to collect claims data from different insurers who use different distribution channels in order to analyze, ceteris paribus, the differences in insurers' portfolio loss according to the way in which the insurance contract was acquired.

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A Appendix

INSTRUCTIONS

You are taking part in an experiment in the context of the **SAF** (Sciences Actuarielle et Financières) research program of the **ISFA** (Institut de Science Financière et d'Assurances) of the University of Claude Bernard Lyon 1.

If you read these instructions carefully you can earn a substantial amount of money. Your final earnings will depend on your decision and the decisions of the other participants in this session. In any case, you will receive a fixed remuneration of 3€ for your participation. Please note that average final earnings are well above this amount. Once the experiment is over, we will give you an attestation of payment that you must sign in exchange for your earnings that will be paid directly and privately in cash.

This experimental session consists of **three independent parts**:

- The first part involves a potential exchange of coins between a **wallet** and a **padded envelope (empty)** that are already on your table.
- The second part consists of 20 questions.
- The third part includes 8 successive independent rounds. In each round, you have to choose an insurance contract in order to be protected against a known risk.

Your final earnings in Euros is the sum of 4 amounts:

- 3 Euros for your attendance.
- The sum of your earnings in each of the three parts.

Communication is forbidden during all the experimental session. If you do not respect this rule, we will cancel this session and you will not be paid. For any questions, please raise your hand.

You will receive an instruction sheet and a comprehension questionnaire (if necessary) at the beginning of each part of this experimental session.

A three-letter login was placed on your table. Please enter your login in order to access the experimental interface.

First part:

During this first part, you will be assigned a type, either A or B. You will keep this type for the entire duration of this experiment. This type defines your role in the different parts.

There is a wallet and a padded envelope (empty) on the table of each participant. Please wait for our signal to open the wallet.

The wallet can:

- Either be **empty.**
- Or contain **10 coins of 50 cents** (5 Euros in total) and **a card** showing the result of 10 independent draws. Each draw is carried out using two balls: green and red.

<u>If your wallet is NOT EMPTY you are a participant of type B:</u>

For this part, **we ask you to apply the following rule:**

- **For each green ball shown, you can take 0.50€ from the wallet and put these 0.50€ in the padded envelope.**
- The remaining Euros in the wallet correspond to **0.50€ times the number of red balls**.

However, the experimenter and the other participants cannot know if you apply this rule. You are not monitored and all wallets are put together in the same bag at the end of this part of the experiment.

For this part, your earnings correspond to the amount that you put in the padded envelope.

PLEASE LEAVE THE SMALL CARD IN THE WALLET

Example : If your card is the following : 

By applying the rule, you:

- Take six 0.50€ coins, and
- Leave four 0.50€ coins in the wallet.

<u>If your wallet is EMPTY you are a participant of type A:</u>

In this part of the experiment, the different draws given to the B participants appear on your screen. You have to indicate for each of these **How much, in Euros, do you think that the B participant left in the wallet?**
To calculate your earnings for this part, we randomly select one of these draws and you will receive:

5 € - |your estimation error |

Example: If the draw selected is the following : 

B actually left 1€ (two 0.50€ coins) in the wallet and you had estimated that 2€ (four 0.50€ coins) would be left. You therefore earn:

5€ - |your error of estimation| = 5€ - |2€ - 1€| = 5€ - 1€ = 4€

Second part:

In this second part we are going to present numbers in ECU (*Experimental Currency Units*). This measure is converted into Euros at the end of the session at the following rate: **1 ECU = 0.02€; 1€ = 50 ECU.**

In this second part, **whatever your type,** you have to answer **two series of 10 questions.** For each question, you should **choose one option (A or B).**

For this part, we will randomly select one question and your earnings will be calculated according to the outcome of your corresponding chosen choice.

Example :

1st possible case: **<u>in the case of a Gain</u>**

Please choose between **A** and **B** for the 10 following questions.

For your earnings, we will randomly select one question and your earnings will be calculated according to the outcome and your corresponding choice.

Option A					Option B				
% chance	Gain	and	% chance	Gain	% chance	Gain	and	% chance	Gain
10 %	50 ECU		90 %	20 ECU	10 %	85 ECU		90 %	5 ECU

You should indicate if:

You prefer a **1-in-10 chance of winning 50 ECU** and a **9-in-10 chance of winning 20 ECU** (Option A)

or

You prefer a **1-in-10 chance of winning 85 ECU** and a **9-in-10 chance of winning 5 ECU** (Option B)

2nd possible case: **<u>in the case of a Loss</u>**

Please choose between **A** and **B** for the 10 following questions.

For each questions you have 100 ECU, questions are independents.

For your earnings, we will randomly select one question and your earnings will be calculated according to the outcome and your corresponding choice.

Option A					Option B				
% chance	Loss	and	% chance	Loss	% chance	Loss	and	% chance	Loss
10 %	40 ECU		90 %	45 ECU	10 %	10 ECU		90 %	80 ECU

You should indicate if, from **100 ECU** :

You prefer a **1-in-10 chance of losing 40 ECU** and a **9-in-10 chance of losing 45 ECU** (Option A)

or

You prefer a **1-in-10 chance of losing 10 ECU** and a **9-in-10 chance of losing 80 ECU** (Option A)

Third part:

This part consists of eight successive independent rounds. The first two rounds are trials and will not affect your earnings. Whatever your type, your earnings in this part correspond to your earnings in one of the six remaining rounds, selected randomly.

You are type A:

In each round, you have an **initial wealth level**, a **probability of loss**, and an **amount of loss**. You have to choose an insurance contract in order to be protected against the loss. **It is compulsory to underwrite a contract**.

Each contract contains:

- A fixed **premium** (this is the price of the contract).
- A **deductible** that you have to pay in the case of loss.

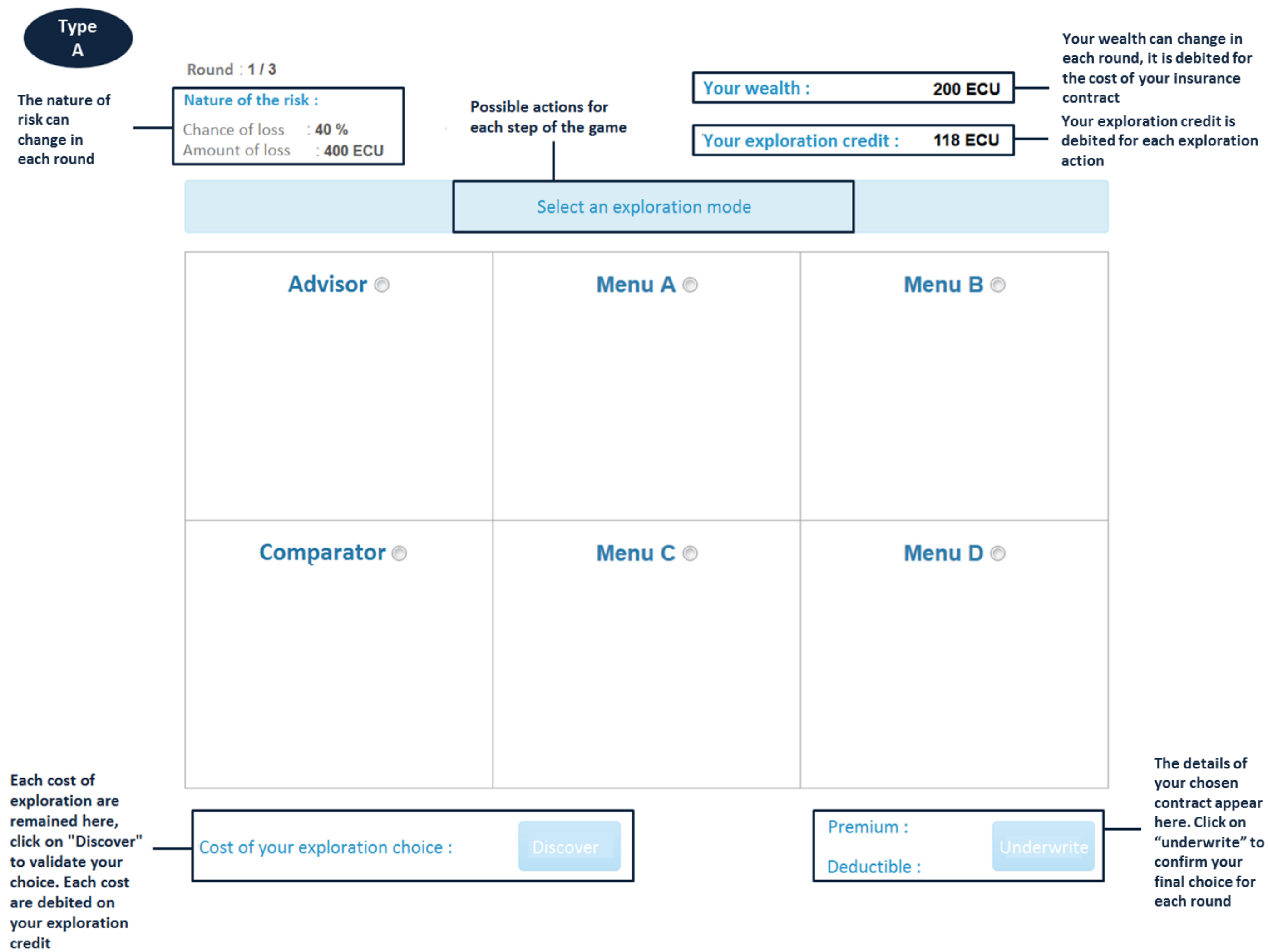
Example: The loss amount is 1000 ECU with a probability of 17% and initial wealth of 180 ECU, If you select an insurance contract with a premium of 70 ECU and a deductible of 25 ECU:

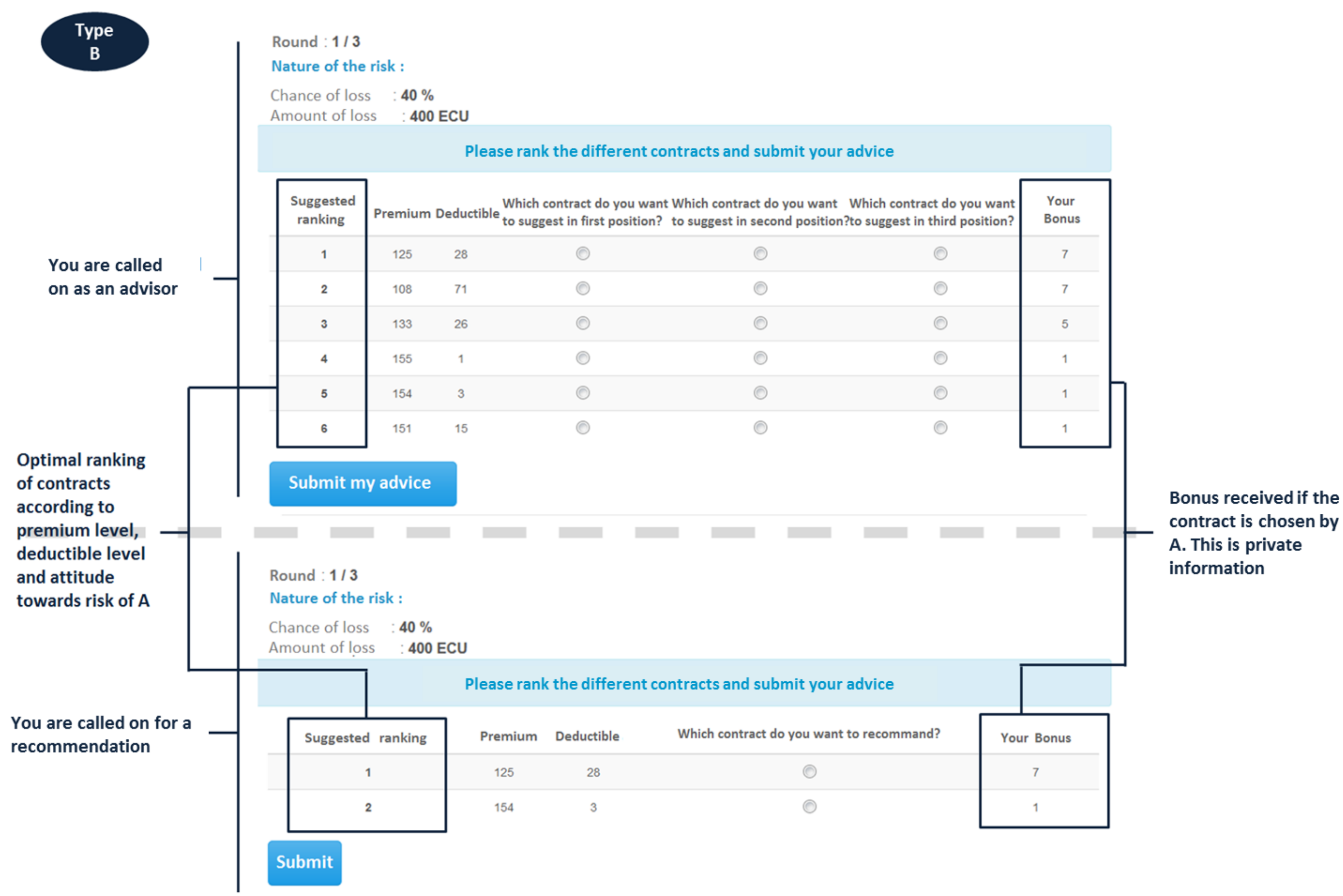
- If the loss occurs (with probability of 17%), you earn: 180 – 70 – 25 = 85 ECU
- If the loss does not occur (with a probability of 83%), you earn: 180 – 70 = 110 ECU

There are **eight different potential contracts**. These contracts are not visible at the beginning of the round, and will partly or fully appear on your screen as you choose different exploration actions. To do so you have an **exploration credit** that is used up according to the different types of exploration you choose. Any unconsumed exploration credit is part of your earnings.

To find out about the potential contracts, you can:

- **Explore one of the four menus (A, B, C and D)**. Each menu consists of 2 contracts. To find out about the contracts in one particular menu you have to pay **12 ECU** (debited from your exploration credit). Once you access this menu, you can ask for a recommendation from a type-B participant. Asking for a recommendation costs **4 ECU** (debited from your exploration credit). Participants of type B are informed of a contract-ranking according to your own attitudes towards risk. In addition, they know the bonus associated with each contract. The B participant receives the bonus associated with the contract if you choose the contract that they recommend for you. The A participants do not know either the contract ranking or the bonuses.
- **Look for an advisor** (i.e. a type-B participant). This costs **12 ECU** (debited from your exploration credit). A type-B participant is randomly selected and will be informed of a contract-ranking covering six different potential contracts (including contracts from three of the four different menus). The ranking is based on your own attitudes towards risk. The B participant knows the bonus associated with each contract. The A participants do not know either the contract ranking or the bonuses. The B participant suggests a ranking of three contracts to participant A. If you choose a contract through the advisor, you will pay **14 ECU** (debited from your initial wealth).
- **Explore via a comparator.** Access to a comparator costs you **12 ECU** (debited from your exploration credit). Six of the eight possible contracts will then appear on your screen (from three of the four menus). However, only the premium information will appear. To find out about the associated deductible you have to pay **3 ECU** per contract. You do not know the ranking of these contracts.


Type A
The nature of risk can change in each round
Round : 1 / 3
Nature of the risk :
Chance of loss : 40 %
Amount of loss : 400 ECU
Possible actions for each step of the game
Your wealth : 200 ECU
Your exploration credit : 118 ECU
Your wealth can change in each round, it is debited for the cost of your insurance contract
Your exploration credit is debited for each exploration action
Select an exploration mode
Advisor
Menu A
Menu B
Comparator
Menu C
Menu D
Each cost of exploration are remained here, click on "Discover" to validate your choice. Each cost are debited on your exploration credit
Cost of your exploration choice :
Discover
Premium :
Deductible :
Underwrite
The details of your chosen contract appear here. Click on "underwrite" to confirm your final choice for each round



Type B
You are called on as an advisor
Optimal ranking of contracts according to premium level, deductible level and attitude towards risk of A
You are called on for a recommendation
Bonus received if the contract is chosen by A. This is private information
Round : 1 / 3
Nature of the risk :
Chance of loss : 40 %
Amount of loss : 400 ECU
Please rank the different contracts and submit your advice
Suggested ranking
Premium
Deductible
Which contract do you want to suggest in first position?
Which contract do you want to suggest in second position?
Which contract do you want to suggest in third position?
Your Bonus
1 125 28 7
2 108 71 7
3 133 26 5
4 155 1 1
5 154 3 1
6 151 15 1
Submit my advice
Round : 1 / 3
Nature of the risk :
Chance of loss : 40 %
Amount of loss : 400 ECU
Please rank the different contracts and submit your advice
Suggested ranking
Premium
Deductible
Which contract do you want to recommand?
Your Bonus
1 125 28 7
2 154 3 1
Submit

__**You are type B:**__

You can be called by a type-A participant in two different ways:

- **If a type A seeks an advisor.** There will appear on the screen of one selected type-B participant a ranking of **six different contracts** (from three of the four menus) and **a bonus associated with each contract**. **This ranking depends on the premium, the deductible and the profile of the type-A participant regarding risk.**

  If you are called here you should **suggest a ranking of three contracts** to type A. If the type-A participant chooses one of the contracts suggested, you earn a **fixed fee of 14 ECU**, paid by type A, and the bonus associated with the chosen contract.

- **If participant A asks for a recommendation**. There will appear on the screen of one selected type-B participant **a ranking of two contracts** and **a bonus associated with each contract.**

  If you are called here you should **recommend only one contract**. If the type-A participant chooses one of these contracts, you earn the associated bonus.

Participant A does not pay the bonus. There is a transfer from A to B only if A chooses a contract through the advisor (a fixed fee of 14 ECU).

For a request from an A participant only one B is randomly selected. It is therefore possible for each B participant to be called once, a number of times or never during a round.

For each round, your **earnings are equal to a fixed remuneration of 120 ECU and the potential additional earnings resulting from interactions with the A participants**. For this part, your final earnings are equal to those in one of the six rounds, randomly chosen.

Thanks for your participation

Before leaving the room to receive your payment, please fill out the final questionnaire. Then, please click on “Validate”.

Before leaving your table, please:

- Take your three-letter login.
- Take all instruction sheets.

Comprehension Questionnaire for Part 1 of the Experiment:

We will mark this questionnaire in a few minutes.

If you are A:

Your wallet contains 5 Euros:	TRUE ☐ FALSE ☐
For each draw, you should indicate the amount in Euros that B left in the wallet:	TRUE ☐ FALSE ☐
For each draw, you should indicate your estimation of the amount that B left in the wallet:	TRUE ☐ FALSE ☐
Your earnings depend only on your estimation:	TRUE ☐ FALSE ☐

If you are B:

Your wallet only contains 5 Euros:	TRUE ☐ FALSE ☐
You have to leave 0.50€ in the wallet for each red ball:	TRUE ☐ FALSE ☐
The experimenter or the A's know the amount that you left in the wallet:	TRUE ☐ FALSE ☐
No-one knows the amount that you left in the wallet:	TRUE ☐ FALSE ☐

Comprehension Questionnaire for Part 3 of the Experiment:

We will mark this questionnaire in a few minutes.

If you are A:

It is possible to return to an exploration design if you have enough exploration credit :	TRUE ☐ FALSE ☐
Your final earnings for this part can depend on the first two rounds:	TRUE ☐ FALSE ☐
The comparator displays the premium and deductible of each contract for free:	TRUE ☐ FALSE ☐
Your initial wealth, the amount of loss, the probability of loss and the exploration credit can change from round to round:	TRUE ☐ FALSE ☐
It is possible to choose a contract without knowing its associated deductible:	TRUE ☐ FALSE ☐
It is possible to choose a contract suggested by the advisor without paying the fixed fee:	TRUE ☐ FALSE ☐
When you choose a contract suggested by the advisor, the fixed fee is debited from your exploration credit:	TRUE ☐ FALSE ☐
If you do not spend your exploration credit, this amount is added to your earnings:	TRUE ☐ FALSE ☐

If you are B:

It is possible to never be called during a round:	TRUE ☐ FALSE ☐
You have to rank contracts in the same order as displayed:	TRUE ☐ FALSE ☐
The ranking displaying on your screen depends only on the bonus:	TRUE ☐ FALSE ☐
The bonus is paid by A:	TRUE ☐ FALSE ☐

B Appendix

Table 4 bis – Multinomial Regression including Random Effect

Explanatory Variable	Intraround Channel Switch					
	Model 5 bis		Model 6 bis		Model 7 bis	
First choice:	Broker		Insurance		Comparator	
Coefficients *Std. error*	Comparator	Insurance	Comparator	Broker	Insurance	Broker
Honesty Belief Level	−2.00 *1.85*	−0.15 *0.74*	0.76** *0.35*	0.52 *2.65*	0.31 *0.28*	0.30 *0.37*
Risk Aversion	0.05 *0.28*	−0.11 *0.28*	−0.04 *0.21*	−0.05 *0.92*	0.31** *0.16*	−0.53 *0.59*
Initial Wealth	0.00 *0.00*	0.00 *0.00*	0.01 *0.01*	0.01 *0.02*	0.00 *0.00*	−0.01 *0.01*
Loss Amount	0.00 *0.00*	0.00 *0.00*	0.00 *0.00*	0.01 *0.01*	0.00 *0.00*	0.00 *0.00*
Probability of Loss	3.28 *4.68*	4.47 *3.96*	−1.69 *4.19*	6.62 *14.47*	4.14* *2.22*	6.33 *2.22*
Round number	−0.29 *0.25*	−0.05 *0.24*	−0.10 *0.25*	0.74 *2.48*	−0.09 *0.16*	−0.49 *0.32*
Deviation Degree	1.67* *0.99*	0.21 *0.38*	−0.35 *2.45*	2.09 *2.31*		
Deviation Deg. and Honesty Belief	1.41* *0.84*	0.47 *0.29*	−0.41 *1.68*	0.06 *0.94*		
Deductible nb. discovered					1.83** *0.47*	−0.92 *0.75*
Constant (ref. level: No Switch)	−9.12 *5.74*	−4.49 *2.13*	−2.91 *2.04*	−14.8 *22.78*	−5.52 *1.80*	−1.14 *2.48*
Nb. Observations	237		210		615	
Nb. Subjects	79		67		140	
R^2	0.293		0.224		0.281	
Adjusted R^2	0.221		0.132		0.256	

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

Table 9 bis – Logistic Regression including Random Effect

Explanatory Variable	**Deviation**	
Coefficients *Std. error*	**Model 21**	**Model 21 bis**
Risk Aversion (loss)	-0.28^{**} *0.09*	-0.29^{**} *0.09*
Initial Wealth	0.01 *0.00*	0.01 *0.00*
Loss Amount	0.00 *0.00*	0.00 *0.00*
Probability of Loss	-2.22 *1.66*	-2.22 *1.73*
Optimal Contract Bonus	-0.05^{*} *0.02*	-0.04^{*} *0.02*
Status: TIED-AGENT	-1.28^{*} *0.68*	-1.30^{*} *0.68*
Dishonesty Session Level	0.59^{**} *0.26*	
Session 1		0.34 *0.48*
Session 2		-0.26 *0.66*
Session 3		-0.98 *1.07*
Session 4		-0.17 *0.77*
Session 5		-1.07 *0.73*
Session 6		-0.94 *0.55*
Session 7		-0.80 *0.53*
Round Number	-0.01 *0.10*	-0.01 *0.10*
Constant (ref. level: NO)	2.66^{**} *0.89*	2.59^{**} *0.95*
Nb. Observations	289	289
Nb. Subjects	40	40
R^2	0.181	0.189
Adjusted R^2	0.152	0.141

Signif. codes for p-values: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1