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# Serving consumers in an uncertain world: A credence goods experiment§

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## Abstract

Credence goods markets are prone to fraudulent behavior and market inefficiencies due to informational asymmetries between sellers and customers. We examine experimentally the effects of diagnostic uncertainty and insurance coverage on the information acquisition and provision decisions by sellers and the trading decisions by consumers. Our results reveal that diagnostic uncertainty is a major source of inefficiency by decreasing efficient service provision. Insurance coverage has a positive net effect on market efficiency, despite making information acquisition and efficient service provision less likely. We also examine the role of -s and of sellers' prosociality in shaping service provision and information acquisition.

JEL-codes: C91, D82, G22

Keywords: Credence goods, diagnostic uncertainty, insurance coverage, experiment

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## 1. Introduction

In markets for credence goods, expert sellers (e.g., doctors, mechanics, legal or financial advisors) are better informed than consumers about the quality of the good, service, or asset that fits consumers' needs best. This informational advantage of sellers creates incentives to cheat consumers – by providing too much (*overtreatment*), too little (*undertreatment*), or charge for more than has been provided (*overcharging*). The incentives for fraudulent behavior may cause large inefficiencies. This is particularly worrisome because credence goods markets have a huge volume. In the U.S.A., for instance, health care services account for about 17% of GDP[1], the finance industry represents about 20% of GDP[2], and car repair services, another prominent example for credence goods, generated total revenues of about 70 billion Dollars in 2019.[3]

In analyzing the informational asymmetries between expert sellers and consumers, most of the existing work assumes that experts can identify their consumers' needs perfectly, and often at no cost (see Balafoutas and Kerschbamer, 2020, for a review of the theoretical and empirical literature on markets for credence goods). In reality, however, this is seldom the case. Diagnosis is usually costly because it requires time and effort, and it may even fail to identify a consumer's problem perfectly (Schneider, 2012). Another common assumption in the literature is that consumers bear the full cost of service. In contrast to this assumption, in many real-world credence goods markets consumers are insured and thus often have zero, or negligible, marginal costs of additional services. This may induce consumers to think themselves safe with respect to potential problems arising from diagnostic uncertainty. However, insurance may reduce the expert's incentives to invest in costly diagnosis, leading to more diagnostic uncertainty. Also, for a given level of diagnostic uncertainty, insurance may lead to less efficient service provision. Conversely, higher uncertainty in the diagnosis and less efficient service provision are likely to increase consumer expenditures, creating a stronger need for insurance coverage.

This paper provides evidence on the role of costly information acquisition, diagnostic uncertainty and insurance coverage in an experimental market for credence goods. It advances our understanding of markets for credence goods by being the first to examine the behavior of expert sellers and consumers in a controlled environment that departs from perfectly informative and costless diagnosis. The environment follows a theoretical companion paper by Balafoutas et al. (2023), which extends previous literature by adding the following four features to the seminal

[1] See http://www.oecd.org/els/health-systems/health-expenditure.htm (accessed 29 September 2023

[2] See the United States' Bureau of Economic Analysis: https://www.bea.gov/data/gdp/gdp-industry (accessed 29 September 2023).

[3] See https://www.ibisworld.com/industry-trends/market-research-reports/other-services-except-public-administration/repair-maintenance/auto-mechanics.html (accessed 29 September 2023).

framework of Dulleck and Kerschbamer (2006): (i) uncertainty in the diagnosis by expert sellers, (ii) insurance of consumers, (iii) malpractice payments when a seller fails to sufficiently address the consumer's needs, and (iv) the possibility that sellers display other-regarding preferences by internalizing part of the consumers' material payoff. These features are key in explaining overtreatment in credence goods markets and especially in healthcare (Lyu et al., 2017). Diagnostic imprecision may induce cautious sellers to provide too much – especially in the presence of malpractice payments or when sellers have other-regarding preferences.[4] The problem might be further aggravated if insurance coverage makes it cheap or costless for consumers to receive too much. Including all of those aspects into a controlled experimental environment promises to provide insights into the performance of real-world credence goods markets.

We formulate a number of predictions based on the model of Balafoutas et al. (2023) and examine the behavior of experts and consumers in an experimental market for credence goods. The lab experiment involves 576 participants and is based on a 3 x 2 factorial design, varying the following factors: (i) *Diagnostic Uncertainty*. Experts receive a costly signal about the consumer's problem that – depending on treatment – is either 100% precise, 70% precise, or of endogenous precision. (ii) *Insurance*. Consumers are either fully insured, i.e., the full price of service is covered by an insurance in return for a premium, or not insured, in which case they have to pay the full price of service themselves. (iii) *Prices*, implementing three price vectors that imply different incentives for experts. The parameterization in the experiment is such that efficiency always requires the expert to follow the signal (in the treatments with exogenous precision) or to acquire a perfectly informative signal and then to follow the signal (in the treatments with endogenous precision). This allows for a direct test of the model's predictions regarding the impact of various factors on information acquisition and efficient service provision.

Our findings largely confirm the main predictions. First, we identify diagnostic uncertainty as a major source of inefficiencies in credence goods markets. Comparing the two treatments that vary the exogenously given diagnostic precision, we find that less precision leads to lower rates of efficient service provision and lower rates of consumer willingness to trade. These effects hold independently of insurance coverage. To the best of our knowledge, these findings provide the first evidence from an experiment on the possible adverse effects of diagnostic uncertainty in markets for expert services. Second, we find strong empirical support for the prediction that insurance coverage reduces the rate of efficient service provision (in the treatments with exogenous precision) and the average investment in diagnostic precision (in the treatment where precision is

[4] Evidence from the lab and the field suggests that (at least some) expert sellers have other-regarding preferences (Liu and Ma, 2013; Brosig-Koch et al., 2016, 2017; Kerschbamer et al., 2017).

endogenous). The net impact of insurance on market efficiency is nevertheless positive, significant and quite sizeable, thanks to the counterbalancing force of more frequent trade from insured consumers. Third, we find that the rate of efficient service provision responds to prices in the predicted way, and it is lowest (highest) when prices are such that experts have incentives to overtreat (undertreat) consumers. Finally, based on an experimental elicitation of distributional preferences one week before the experiment, we find that more prosocial experts are more likely to invest in diagnostic precision, all else equal.

There is only a small set of papers that theoretically address endogenous information acquisition in credence goods markets (Pesendorfer and Wolinsky, 2003; Dulleck and Kerschbamer, 2009; Bester and Dahm, 2018; Liu et al., 2019), and no controlled empirical evidence on this topic. Also, there is only a handful theoretical papers that analyze the role of diagnostic uncertainty on provision behavior (Inderst and Ottaviani 2012; Fong et al. 2022; Baumann and Rasch 2023), and no laboratory evidence on this issue. Our experiment closes those gaps. Turning to the theoretical literature on the role of insurance, Sülzle and Wambach (2005) show that increasing the degree of coinsurance by the consumer can increase or decrease the likelihood of overcharging by the expert seller, depending on the parameters. There are several experimental studies on how insurance coverage affects sellers' and consumers' behavior in credence goods markets. In a laboratory experiment, Huck et al. (2016) find that insurance coverage lets consumers ask for more treatments, and sellers are more likely to overtreat consumers. Three field experiments confirm these patterns. Lu (2014) studies physicians' prescription behavior and reports that doctors write significantly more expensive prescriptions to insured patients. Kerschbamer et al. (2016) find that notebook owners with an insurance are charged about 80% more than non-insured owners for getting a notebook repaired, and Balafoutas et al. (2017) report a similar pattern in the market for taxi rides. However, none of these papers test predictions arising directly from a theoretical model that builds insurance into a credence goods market. Moreover, the literature has, so far, dealt with the effects of diagnostic uncertainty and insurance coverage in completely separate lines of research, thus ignoring how these two prominent factors might interact with each other in credence goods markets. Here, we opt for a treatment variation that includes both factors and analyze the behavior of sellers and consumers in an environment that is as comprehensive as possible.

The rest of the paper is organized as follows: Section 2 summarizes the main elements of the model and the main results in Balafoutas et al. (2023). Section 3 introduces our experimental design and Section 4 derives the testable predictions. Section 5 presents the experimental results and Section 6 concludes the paper.

## 2. Theoretical Framework and Results

### 2.1. Main Elements of the Model by Balafoutas et al. (2023)

In this section we summarize the main elements of the model by Balafoutas et al. (2023), which forms the basis for our experimental design and predictions. In the model, each consumer (he) has either a major problem requiring a high-quality service (HQS) at cost $\overline{c}$, or a minor problem requiring a low-quality service (LQS) at cost $\underline{c}$, with $\overline{c} > \underline{c}$. The consumer knows that he has an *ex ante* probability $h$ of having the major problem and a probability of $1 - h$ of having the minor one. The consumer derives utility $v > 0$ when his problem is solved through a service provided by the expert, and zero utility otherwise. While the HQS solves both problems, the LQS solves only the minor problem. The consumer can observe and verify the kind of service he receives, but he only finds out whether the received quality was the needed one when the expert provides the LQS for the major problem (since in that case his problem remains unsolved). In case a consumer does not receive a service, both he and the expert receive a reservation utility of $o \in [0, v)$.

*Ex ante* the expert (she) has the same information as the consumer on the severity of the consumer's problem. In contrast to the consumer, the expert is able to acquire additional information about the consumer's problem by performing a diagnosis. We consider two cases, one with exogenous diagnostic precision (abbreviated as *EXO*) and one with endogenous precision (abbreviated as *ENDO*). In *EXO* the expert receives a signal about the severity of the consumer's problem which is correct with some exogenous probability. In ENDO the expert can freely decide whether to acquire additional information at some cost knowing that cost is increasing and convex in the precision level. If the expert does not acquire any information she receives a completely uninformative signal. In both cases (*EXO* and *ENDO*), the expert faces a penalty $t \in (0, v)$ whenever she prescribes the LQS to a consumer having the major problem. This payment is a transfer from the expert to the consumer as compensation for service failure.

Let the exogenously given prices for LQS and HQS be denoted by $\underline{p}$ and $\overline{p}$. The price markups for LQS and HQS are defined as $\underline{\Delta} = \underline{p} - \underline{c}$ and $\overline{\Delta} = \overline{p} - \overline{c}$, respectively. Balafoutas et al. (2023) distinguish between three types of price vectors: (i) overtreatment (OT) price vectors, where the markup for HQS exceeds the LQS markup ($\overline{\Delta} > \underline{\Delta}$); (ii) undertreatment (UT) price vectors, with the LQS markup being higher than the HQS one ($\overline{\Delta} < \underline{\Delta}$); and (iii) equal markup (EM) price vectors, with $\overline{\Delta} = \underline{\Delta}$.

The model allows for the possibility that the expert cares positively about the consumer's well-being: The expert maximizes his own material payoff (weighted by one) plus $\lambda$ times the consumer's surplus, $\lambda \in [0,1]$. A positive value of $\lambda$ characterizes a prosocial expert, while $\lambda = 0$ implies that the expert is completely selfish.[5] The expert knows her $\lambda$, while the consumer knows only the distribution of this parameter in the population of experts.

**2.2. Theoretical Results for EXO**

For the case of exogenous precision, Balafoutas et al. (2023) show that there are three candidates for the efficient strategy by expert sellers (defined as the strategy that minimizes the direct costs of providing a given service plus the implied utility loss for the case where the service fails):

Strategy A: *Implement the HQS independently of the outcome of the diagnosis*.

Strategy B: *Implement the LQS independently of the outcome of the diagnosis*.

Strategy C: *Implement the LQS if the signal suggests that the problem is minor and implement the HQS if the signal suggests that the problem is major*.[6]

Intuitively, Strategy C is efficient if the diagnosis is sufficiently precise and if the likelihood of suffering from the major problem is neither close to 1 (in this case Strategy A is efficient) nor close to 0 (where Strategy B is efficient). Arguably the most interesting setting is the one where Strategy C is efficient. For this setting (and additionally assuming that Strategy A is more efficient than Strategy B) the authors show that EM prices only lead to efficient service provision for all expert types if the signal is fully precise. In the presence of diagnostic uncertainty, EM prices will induce selfish and moderately altruistic experts to decide for Strategy A for any $t > 0$ because following the imprecise signal carries the risk of paying the compensation payment (in case of failure) while Strategy A is safe in this respect. UT prices combined with a positive transfer are more robust – if well designed they yield efficient provision for all precision levels and expert types. For given prices, diagnostic imprecision unambiguously leads to less efficient provision: Under EM, OT und mild UT price vectors a less precise signal induces selfish and moderately altruistic expert to decide for Strategy A instead of Strategy C as A avoids the transfer in case of failure while C does not. Under pronounced UT price vectors more diagnostic uncertainty induces selfish and moderately altruistic experts to choose Strategy B instead of Strategy A because with a less precise

[5] Negative values of $\lambda$ correspond to spiteful experts. Empirically, they are very rare (< 2%) in our experiment.

[6] There is a fourth possible pure strategy, in which the expert provides a treatment opposite to the signal she receives. We ignore this strategy in the remainder of the paper, since Balafoutas et al. (2023) show that it is dominated by one of the other three strategies for any given constellation of the parameters.

signal there is hope that the LQS (with the higher markup) solves the problem (and thereby avoids the transfer) while with full precision there is no such hope.

The impact of insurance on efficient provision depends on the prices for LQS and HQS: Under OT, EM and mild UT price vectors the introduction of insurance unambiguously leads to less efficient provision, while under pronounced UT prices the effect of introducing insurance is ambiguous. The negative effect of introducing insurance on efficient provision is due to the fact that in the presence of diagnostic uncertainty the customer profits from always receiving the HQS as the signal is imprecise and as the additional cost of always providing the HQS is covered by the insurance.

The effect of altruism on efficient provision is positive without insurance, but ambiguous in the presence of insurance. Without insurance more altruistic experts tend to implement Strategy C – without diagnostic uncertainty because Strategy C is unambiguously in the interest of the consumer, and with diagnostic uncertainty because the additional benefit of Strategy A (making sure that the problem is solved for sure) is not enough to justify the additional cost. In the presence of insurance more altruistic experts tend to implement Strategy A because this strategy provides more benefits to the consumer and because the additional cost is covered by the insurance company. In the presence of insurance there might be a countervailing effect under pronounced UT price vectors. We do not discuss this somewhat exotic case further as it will be irrelevant for the parameters we implement in our experiment.

**2.3. Theoretical Results for ENDO**

For the case with endogenous information acquisition there are again three candidates for an efficient solution. Strategies A and B (now defined as "*Implement the HQS without acquiring additional information*", and "*Implement the LQS without acquiring additional information*"), and Strategy C': "*Invest the efficient amount in information acquisition and then follow the signal obtained*". Intuitively, Strategy C' is efficient if the cost of acquiring information is not too high and if the likelihood of the major problem is neither close to 1 nor close to 0. Similar to the EXO case, for the case where Strategy C' is efficient positive investments in information acquisition for all expert types can only be induced by UT prices combined with a well-designed transfer (but not by EM or OT price vectors). The intuition is similar to the EXO case. Also similar to the EXO case, under OT, EM and mild UT price vectors introducing full insurance unambiguously leads to lower investments in information acquisition as experts are tempted to implement Strategy A which provides benefits to the consumer while the costs are borne by the insurance company.[7] Again, the effect of altruism on information acquisition is positive without insurance, but ambiguous in the presence of insurance.

## 3. Experimental Framework and Design

Since other-regarding preferences of experts play a role for their market behavior in the theoretical framework of Balafoutas et al. (2023) we elicit the social preferences of our subjects in the first (online) part of the experiment. In the second (lab) part, subjects play the credence goods game sketched in the theory section.

### 3.1. Online Part (Elicitation of Social Preferences)

After subjects registered for an experimental session, they received a link for the online part of the experiment that was run before the lab session. In the online part we elicited social preferences by means of the Equality Equivalence Test, henceforth EET (Kerschbamer, 2015). The EET exposes subjects to two choice lists, one located in the domain of advantageous inequality and the other in the domain of disadvantageous inequality. The switching points of a subject in the two lists are used to infer the subject's prosociality (the parameter $\lambda$). This parameter is measured separately for each domain. For the domain of disadvantageous inequality we denote the inferred $\lambda$ as $\lambda_D$, and for the domain of advantageous inequality we denote it as $\lambda_A$. The parameters of the EET and the details of the calculation of $\lambda$ are provided in Appendix A. Decisions were incentivized and participants were paid after the lab part had also been concluded. All experimental instructions are provided in Appendix B.

### 3.2. Lab Part (The Market Experiment)

We implement the following parameters in the market experiment: $h = 0.4$, $v = 150$, $t = 50$, $o = 15$. The cost of providing the LQS is $\underline{c} = 20$ and the cost for the HQS is $\overline{c} = 60$. We fix the price of the LQS across all price vectors at $\underline{p} = 60$ and vary the type of price vector through the price of the HQS. Specifically, for UT we set $\overline{p} = 80$; for EM we set $\overline{p} = 100$; and for OT we set $\overline{p} = 120$. Hence, the three types of price vectors have the following markups of prices over costs: (i) UT: $\underline{\Delta} = 40$, $\overline{\Delta} = 20$; (ii) EM: $\underline{\Delta} = \overline{\Delta} = 40$; (iii) OT: $\underline{\Delta} = 40$, $\overline{\Delta} = 60$.

[7] Only under pronounced UT price vectors (not relevant for the parameters implemented in our experiment) the effect of introducing insurance on information acquisition is ambiguous.

The experimental treatments are presented in Table 1. We implement three conditions with respect to diagnostic precision in a between-subjects design, and two insurance conditions in a within-subjects design. Regarding diagnostic precision, in **EXO100** the expert receives a fully precise signal about the consumer's problem; in **EXO70** the expert receives a signal that is 70% precise; and in **ENDO**, the expert can choose between six different precision levels (in 10% steps from 50% to 100%). The signal is costly in all cases and the cost follows the function $D(\sigma) = 40(\sigma - 0.5)^2$, where $\sigma$ is the precision level.[8] Hence, the price of diagnostic precision ranges from 0 for $\sigma = 0.5$ to 10 for $\sigma = 1$. In EXO100 and EXO70, the cost of the corresponding signal is automatically subtracted from the expert's profit. In ENDO, the cost is subtracted only if the expert decides to invest in precision. Otherwise, without any investment, she receives an uninformative, costless signal of 50% precision.

***Table 1.*** *Summary of experimental design*

| Treatment | Diagnostic precision | Insurance | Price vectors |
|---|---|---|---|
| EXO100 | 100% | 12 periods with and 12 periods without insurance | 8 periods for each of UT, EM, OT |
| EXO70 | 70% | 12 periods with and 12 periods without insurance | 8 periods for each of UT, EM, OT |
| ENDO | expert chooses among {50%, 60%, 70%, 80%, 90%, 100%} | 12 periods with and 12 periods without insurance | 8 periods for each of UT, EM, OT |

The second treatment variation refers to insurance: In the three **NI** (No Insurance) conditions, the price for the service is fully paid by the consumer if he trades on the market; in the three **FI** (Full Insurance) conditions, the price for the service is entirely covered by an insurance institution in return for a premium paid by the consumer. This premium is set to $P = 80$, which was calibrated based on pilot data in order to ensure zero profits for the insurance institution in expectation. The two insurance conditions are varied within subjects such that a group played 12 periods with insurance and 12 periods without, in blocks of six periods and with balanced ordering. Hence, within each of the three diagnostic precision treatments, we vary two insurance schemes (NI, FI), three types of price vectors (UT, OT, and EM), and the type of the consumer's problem (minor or major). This results in 12 possible combinations of insurance, price vector, and

[8] In Balafoutas et al. (2023) the expert receives the diagnosis for free in the EXO environment. Assuming instead that the signal is costly in all cases does not change any of the derivations. We decided to make the signal costly here in order to keep the EXO and ENDO treatments more comparable.

consumer’s problem. We implemented each of these combinations twice within one session, yielding a total of 24 periods. We find no order effects with regards to the sequence of the different combinations; therefore, we pool all orders in the analysis.

At the beginning of each period, both players were informed about the prevailing price vector and insurance condition. Each period then consisted of three different stages. In Stage 1, the consumer decided whether or not to trade on the market. At the same time the expert received a signal on the consumer’s problem in EXO100 and EXO70, while in ENDO she decided how much to invest in diagnostic precision and afterwards received the signal with the chosen precision. In Stage 2, the consumer was inactive while the expert decided on the quality of the service using the strategy method (i.e., this decision was implemented if the consumer had accepted to trade). In Stage 3, both players were informed about their own payoff.[9] From the second period onwards, experts and consumers could see the history of their own decisions and payoffs from previous periods, but had no information about their previous interaction partners. After the 24 periods of the market game, we elicited participants’ risk attitudes using a validated survey measure (Dohmen et al., 2011), based on a simple question that asked them to report their risk tolerance on a scale from 0 (“completely risk averse”) to 10 (“completely risk-seeking”). Moreover, we collected data on their gender, age, study program, and highest educational degree.

### 3.3. Procedure

We conducted our experiment in the Innsbruck EconLab with students enrolled at the University of Innsbruck. All experimental sessions were computerized with oTree (Chen et al., 2016) and we recruited subjects via H-ROOT (Bock et al., 2014). A total of 576 students participated in the experiment. The number of participants in a session was either 16 or 24. Given that the stage game is repeated for 24 periods, the matching protocol of participants is important. We used matching groups of eight participants, with four experts and four consumers (in fixed roles). Consumers and experts were randomly re-matched within a matching group after each period. This means that the entire interaction in a session over the course of the experiment took place within a matching group, while there were no interdependencies across groups. Accordingly, we use matching groups as independent observations in our statistical tests and cluster for matching groups in our regressions. Table 2 shows the number of participants, sessions, and matching groups per treatment.

[9] The consumer was not informed about the quality that was actually needed, but in case of undertreatment he could infer from the payoff that insufficient quality had been provided.

**Table 2.** *Observations*

| Treatment | Subjects | Observations | Sessions | Matching Groups |
|---|---|---|---|---|
| EXO100 | 200 | 4,800 | 9 | 25 |
| EXO70 | 192 | 4,608 | 8 | 24 |
| ENDO | 184 | 4,416 | 8 | 23 |
| Total | 576 | 13,824 | 26 | 72 |

All parameters, the underlying treatment condition, as well as the matching procedure were made common knowledge to participants by reading them out aloud at the beginning of each session. The average session duration was 1.5 hours and all payoffs were stated in ECU (experimental currency units). Participants received 80 ECU as starting endowment, and earned on average a total of €18.34 (exchange rate 80 ECU = €1) from the online part and all 24 periods in the lab.

## 4. Experimental Predictions

Our parameterization guarantees that Strategy C is the efficient solution in the EXO treatments and that Strategy C' with a fully precise signal is the efficient solution in the ENDO treatments. Also, for all price vectors the impact of insurance on information acquisition and efficient provision is predicted to be unambiguously negative (see subsections 4.1 and 4.2 for details). More detailed predictions for the behavior of sellers and consumers in the experiment are derived below.[10] We begin by analyzing the behavior of sellers in subsections 4.1 and 4.2. Given the model's complexity and the various factors that affect service provision by sellers, the derivation of experimental predictions (across treatments, price vectors, and levels of seller altruism) is shown graphically (in figures 1 and 2). Section 4.3 then derives the predictions for trading decisions by consumers.

### 4.1. Predictions for the Provision Strategy in the EXO Treatments

Figure 1 characterizes the predicted service provision policy for the EXO treatments. The solid lines (blue for the UT price vector, red for the EM price vector and orange for the OT price vector) define the provision areas for the NI case. These lines are based on equations (3) and (4) in the model by Balafoutas et al. (2023), adapted to the parameters of our experiment. The expert decides

[10] The predictions for the EXO treatments follow from the model of Balafoutas et al. (2023), by adapting it to the parameters used in the experiment. For the ENDO treatments, the predictions are gathered used similar techniques.

for Strategy A for parameter combinations lying below the respective line and for Strategy C for parameter combinations above the line. The two black solid horizontal lines (at $\sigma = 1$ and at $\sigma = 0.7$) are the provision lines for the two precision levels implemented in EXO. As can be seen in the figure, with the fully precise signal (upper black solid horizontal line) all expert types decide for efficient service provision (Strategy C) under the UT and the EM price vector, but not under the OT price vector. Under the latter, only fairly altruistic experts decide for Strategy C, while selfish and moderately altruistic experts choose Strategy A. In the presence of diagnostic uncertainty (lower black solid horizontal line) the UT price vector still induces efficient provision for all expert types, but EM and OT induce most types (except for the very altruistic ones) to decide for Strategy A.

The blue, red and orange arrows – derived from equations (5) and (6) in Balafoutas et al. (2023) – illustrate the effect of introducing insurance under the UT, EM and OT price vectors, respectively. In the FI case, all experts decide for Strategy A under the EM and the OT price vector, while for the UT price vector the dashed blue line defines the provision areas (Strategy A below the line and Strategy C above the line).

From Figure 1 we see that, independently of the level of diagnostic precision and of whether insurance is present or absent, a weakly larger range of $\lambda$ values is in Area C under the UT than under the EM price vector, and a weakly larger range of $\lambda$ values is in Area C under the EM than under the OT price vector.[11] We therefore arrive at the following prediction:

***Prediction 1 (impact of price vector on provision strategy in EXO):*** *Independently of the level of diagnostic precision and of whether insurance is present or absent, experts decide for the efficient service provision policy (of following the signal) more frequently under the UT than under the EM price vector, and more frequently under the EM than under the OT price vector.*

Turning to the impact of diagnostic precision on the expert's provision strategy we see that, for each price vector and for both insurance regimes, a larger range of $\lambda$ values is in Area C on the upper ($\sigma = 1$) line than on the lower ($\sigma = 0.7$) line.[12] This leads to the second prediction:

***Prediction 2 (impact of diagnostic precision on provision strategy in EXO):*** *Independently of the price vector and of whether insurance is present or absent, experts decide for the efficient service provision policy more frequently under* $\sigma = 1$ *than under* $\sigma = 0.7$.

[11] Under NI the relation between UT and EM is strict for $\sigma = 0.7$ (while all experts are predicted to choose Strategy C under both price vectors for $\sigma = 1$), and the relation between EM and OT is strict for both precision levels. Under FI the relation between UT and EM is strict for both precision levels, while the relation between EM and OT is strict for none.

[12] Under NI the relation is strict for the EM and OT price vector, while in FI it is strict only for the UT price vector.

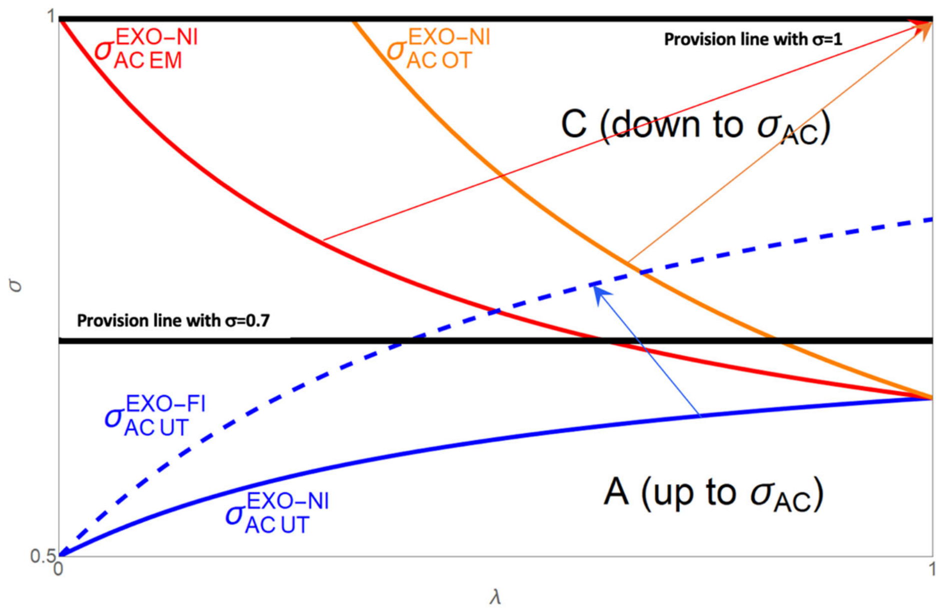
Next we compare – for each price vector and for each provision line – the provision strategy under NI with the one under FI. We see that, in all comparisons, a strictly larger range of $\lambda$ values is in the C-area under NI than under FI. This leads to the third prediction:

***Prediction 3 (impact of insurance on provision strategy in EXO):*** *Independently of the price vector and the level of diagnostic precision, experts decide for the efficient service provision policy more frequently under NI than under FI.*

A final interesting comparison for the EXO case regards the impact of the prosociality parameter λ on the expert's provision strategy. Looking at Figure 1 we see that, under NI, more prosocial experts are weakly more inclined to choose Strategy C than less prosocial ones. Under FI, however, the relationship is reversed.[13] We thus conclude:

***Prediction 4 (impact of prosocial motivation on provision strategy in EXO):*** *Independently of the price vector and of the level of diagnostic precision, under NI more prosocial experts decide for the efficient service provision policy more frequently than less prosocial ones, while under FI the relationship is reversed.*

***Figure 1.*** *Expert's provision in EXO*




**Note:** The figure characterizes the predicted provision behavior for the EXO treatments of the experiment. The two black solid horizontal lines (at $\sigma = 1$ and at $\sigma = 0.7$) are the provision lines for the two precision levels implemented in EXO. The blue, red and orange arrows illustrate the effect of introducing insurance under the UT, EM and OT price vectors, respectively.

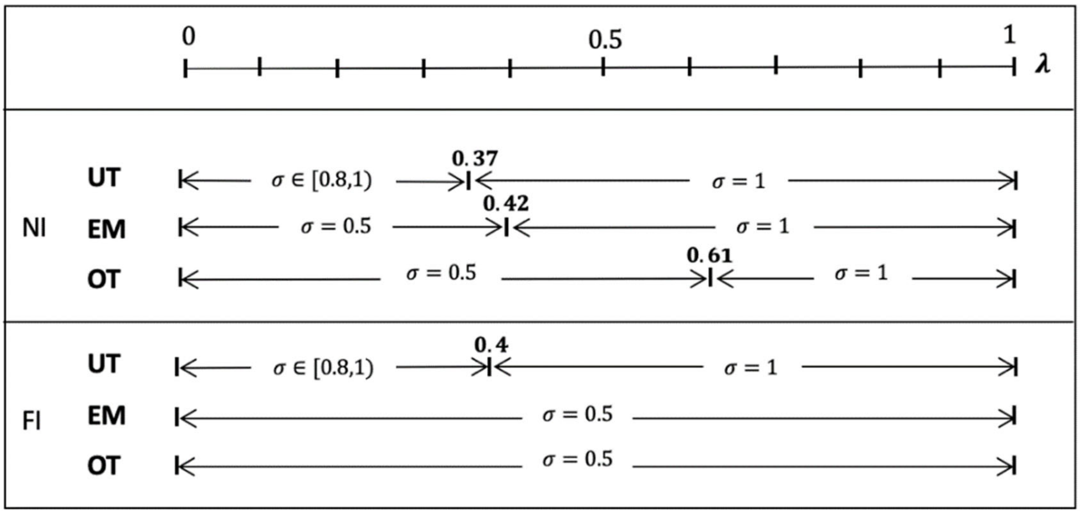
[13] Under NI the relationship is strict for the OT price vector under $\sigma = 1$ and for the OT and the EM price vector under $\sigma = 0.7$, while under FI the (reversed) relationship is strict for the UT price vector under $\sigma = 0.7$.

## 4.2. Predictions for the Investment in Information Acquisition in ENDO

Figure 2 characterizes the expert's investment in information acquisition and her provision behavior for the ENDO treatments. As indicated earlier, for the parameters implemented in the experiment efficiency prescribes to acquire a fully precise signal ($\sigma = 1$) and to follow the signal. In Figure 2 we see that in the NI case altruistic experts (with a $\lambda > 0.61$) decide for efficient information acquisition for all three price vectors. This is no longer the case under FI where even very altruistic experts do not acquire information (and decide for Strategy A) under the EM and the OT price vector. We also see that in both insurance regimes and for all $\lambda \in [0,1]$, the investment in information acquisition is weakly higher under the UT price vector than under the EM price vector and weakly higher under the EM than under the OT price vector.[14] This leads to the following prediction:

***Prediction 5 (impact of price vector on investment in diagnostic precision in ENDO):*** *Independently of whether insurance is present or not, average investment in diagnostic precision is higher under the UT price vector than under the EM price vector, and higher under the EM price vector than under the OT price vector.*

***Figure 2.*** *Expert's investment in information acquisition in ENDO*




**Note:** The figure characterizes the expert's investment in information acquisition and her provision behavior in ENDO. For each insurance regime and each price vector, the figure characterizes the chosen precision level for each $\lambda$ in $[0, 1]$. In constellations where $\sigma > 0.5$ the expert invests in diagnostic precision and then follows the signal. In constellations where $\sigma = 0.5$ the expert abstains from investing and chooses Strategy A.

[14] Under NI the relation between UT and EM is strict for all $\lambda \leq 0.42$ and the relation between EM and OT is strict for all $\lambda \in (0.42, 0.61)$. Under FI the relation between UT and EM is strict for all $\lambda \in [0,1]$, while the relationship between EM and OT is strict for none.

Comparing the two insurance regimes we see that, for all price vectors and all $\lambda \in [0,1]$ the investment in information acquisition is weakly higher under NI than under FI.[15] This leads to the next prediction:

***Prediction 6 (impact of insurance on investment in diagnostic precision in ENDO):*** *Independently of the price vector, the average investment in diagnostic precision is higher (and thereby closer to the efficient level) in NI than in FI.*

Our last prediction for the experts' behavior in the ENDO treatments regards the impact of the parameter λ on investment in information acquisition. Looking at Figure 2 we see that, independently of the price vector and the insurance regime, investment in information acquisition is higher for more prosocial experts than for less prosocial ones.[16] We conclude from this:

***Prediction 7 (impact of prosocial motivation on investment in diagnostic precision in ENDO):*** *Independently of the price vector and of insurance being present or absent, the average investment in diagnostic precision is non-decreasing in the expert's prosociality.*

### 4.3. Predictions for Consumer Behavior in EXO and ENDO

Next, we turn to consumers' trading decisions. For a given environment (EXO100, EXO70 or ENDO), given insurance regime (NI vs FI) and given price vector (UT, EM or OT) the consumer can infer for each $\lambda \in [0,1]$ the expert's investment in diagnostic precision (in the ENDO environment) and her provision behavior (in all environments). He then uses his prior on $\lambda$ to decide whether trade on the market is profitable. Let us start with the EXO treatments. In his trading decision the consumer takes into account that under Strategy A his payoff is $v - \overline{p} = 150 - \overline{p}$ for both diagnostic precision levels, while his payoff under Strategy C depends on the diagnostic precision: For $\sigma = 1$ the consumer's payoff under Strategy C is $v - (1-h)\underline{p} - h\overline{p} = 150 - 0.4\underline{p} - 0.6\overline{p}$, while for $\sigma = 0.7$ it is $[1 - h(1-\sigma)]v + h(1-\sigma)t - (h + \sigma - 2h\sigma)\underline{p} - (1 - h - \sigma + 2h\sigma)\overline{p} = 138 - 0.54\underline{p} - 0.46\overline{p}$. Thus, since $\overline{p} > \underline{p}$ for any given price vector, the consumer unambiguously prefers Strategy C over Strategy A if the signal is perfect; however, under $\sigma = 0.7$ the consumer prefers Strategy C over Strategy A only if $0.54\left(\overline{p} - \underline{p}\right) \geq 12$. Given

[15] Under the UT price vector the relation is strict for all $0.37 < \lambda < 0.4$, under the EM price vector it is strict for all $\lambda \geq 0.42$, and under the OT price vector it is strict for all $\lambda \geq 0.61$.

[16] Under NI, the relationship is strict for all price vectors while under FI the relationship is strict only for the UT price vector.

our parametrization, this latter inequality is satisfied for the EM and the OT price vector, but not for the UT vector. What can we conclude from this?

First consider the case where $\sigma = 1$. This case yields a clear prediction: As we move from the UT to the EM and then to the OT price vector, the range of $\lambda$ values for which Strategy C is provided decreases and at the same time $\overline{p}$ increases. This is unambiguously bad news for the consumer. However, when moving from the UT to the EM price vector for $\sigma = 0.7$, we have two opposing effects. On the one hand, the range of $\lambda$ values for which Strategy C is implemented decreases, which is now good news for the consumer. On the other hand, the price $\overline{p}$ increases, which is again bad news for him. Which of the two price vectors is preferred by the consumer depends on a comparison between his payoff from Strategy C under the UT price vector and his payoff from Strategy A under the EM price vector. This comparison shows that the consumer strictly prefers Strategy C under the UT price vector over Strategy A under the EM price vector, since $138 - [0.54] \cdot 60 - [0.46] \cdot 80 > 150 - 100$. Using similar arguments for the impact of insurance and for the impact of diagnostic precision and also considering the case where the diagnostic precision is endogenous we arrive at the following prediction:

***Prediction 8 (factors affecting consumer's trading decision in EXO and ENDO):***

*(a) Both in EXO and in ENDO, consumers are more likely to trade on the market under the UT than under the EM price vector, and more likely under the EM than the OT price vector. In both settings this prediction holds independently of whether insurance is in place, and in EXO it also holds independently of the level of diagnostic precision.*

*(b) Both in EXO and in ENDO, consumers are more likely to trade on the market under FI than under NI. In both settings this prediction holds independently of the price vector, and in EXO it also holds independently of the level of diagnostic precision.*

*(c) In EXO, consumers are more likely to trade on the market if the diagnostic precision is 100% rather than 70%. This prediction holds independently of the price vector and of whether insurance is in place.*

## 5. Results

Table 3 provides summary statistics about participants as well as for mean earnings, by treatment and overall. Importantly, randomization across the three treatments was successful in every dimension ($p > 0.05$ for all variables; $\chi^2$ tests and Kruskal-Wallis tests).

*Table 3. Summary statistics, by experimental treatment*

| | All | N | EXO100 | N | EXO70 | N | ENDO | N |
|---|---|---|---|---|---|---|---|---|
| *Age (in years)* | 22.66<br>(3.51) | 576 | 22.47<br>(3.26) | 200 | 22.86<br>(4.00) | 192 | 22.66<br>(3.22) | 184 |
| *% Female* | 51.56 | 576 | 56.00 | 200 | 48.96 | 192 | 49.46 | 184 |
| $\lambda_D$ | 0.10<br>(0.36) | 247 | 0.08<br>(0.37) | 86 | 0.05<br>(0.38) | 83 | 0.17<br>(0.29) | 78 |
| $\lambda_A$ | 0.39<br>(0.36) | 247 | 0.41<br>(0.39) | 86 | 0.42<br>(0.37) | 83 | 0.33<br>(0.31) | 78 |
| *Risk Measure* | 5.59<br>(2.11) | 528 | 5.33<br>(2.10) | 176 | 5.72<br>(2.04) | 192 | 5.72<br>(2.20) | 160 |
| *Average payment experts in €* | 14.41<br>(1.39) | 288 | 13.94<br>(1.29) | 100 | 14.74<br>(1.25) | 96 | 14.57<br>(1.51) | 92 |
| *Average payment consumers in €* | 22.26<br>(2.35) | 288 | 23.78<br>(1.83) | 100 | 20.70<br>(1.92) | 96 | 22.24<br>(2.19) | 92 |

Notes: Means for all variables, except *Female*, which refers to the percentage of female subjects. *Risk Measure* is constructed from responses to a survey question on a scale from 0 "completely risk averse" to 10 "fully risk seeking" and is available for participants in all but one session. $\lambda_D$ and $\lambda_A$ are elicited in the EET and range from -5/6 to 5/6, with higher values indicating stronger prosociality. These variables are reported for experts and are missing for 41 subjects, for whom choices in the online part of the experiment could not be matched to the lab part. Standard deviations in parentheses.

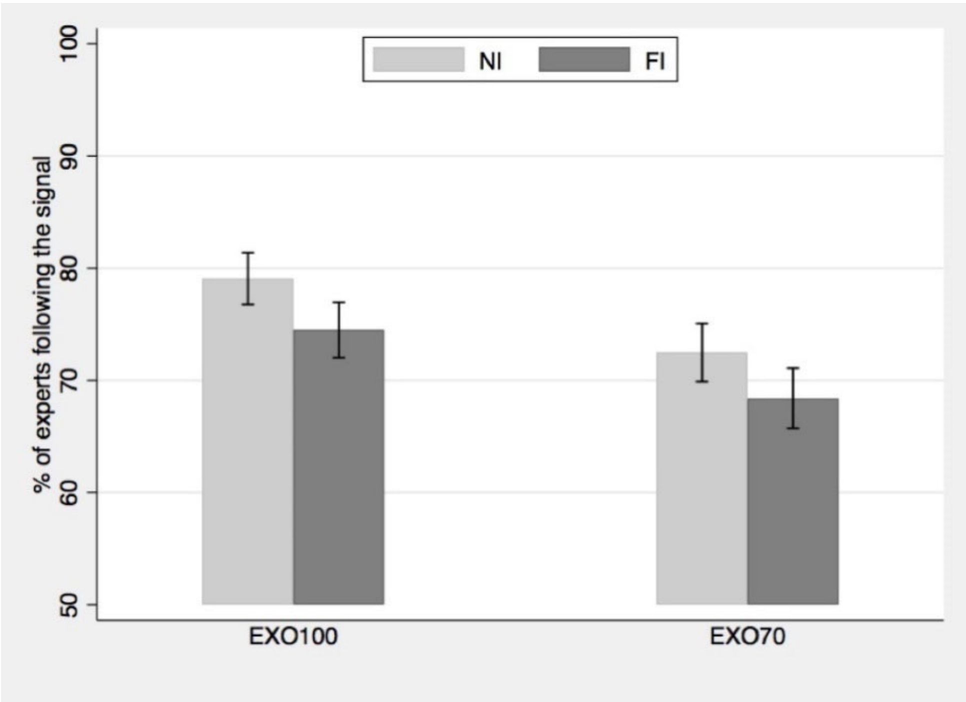
### 5.1. Impact of Prices, Diagnostic Uncertainty and Insurance on Provision Policy (EXO)

We begin by testing predictions 1-3 for the EXO treatments. The main variable of interest is the rate of *efficient service provision*: This is the frequency (or, in the regressions, the likelihood) with which experts decide for the efficient provision policy by following the signal they received.

Prediction 1 relates efficient service provision to prices. In line with this prediction, the share of experts who follow the signal (pooling the two exogenous treatments and the two insurance conditions) is highest with the UT price vector (84.1%), intermediate with the EM price vector (72.5%), and lowest with the OT price vector (64.4%). The difference to the EM vector is significant both for the UT and the OT vector ($p < 0.01$, $\chi^2$-tests).

Figure 3 shows the rate of efficient service provision broken down by diagnostic precision and insurance. The treatment differences support Predictions 2 and 3. In both insurance regimes, efficient service provision is more frequent in EXO100 than in EXO70 (pooled rates 76.8% vs. 70.4%, $p < 0.01$, $\chi^2$ test). This result confirms the negative impact of diagnostic uncertainty on the rate at which expert sellers follow the signal that they receive. In line with Prediction 2, this impact is negative independently of whether insurance is present or absent, and independently of the price vector.[17] Turning to Prediction 3, the data confirm that the rate of efficient service provision declines when insurance is in place (FI) compared to when this is not the case (NI), dropping from 75.9% to 71.5% on aggregate ($p$ = 0.04, $\chi^2$ test). This effect is slightly more pronounced when diagnostic precision is high, but it generally does not retain its significance when disaggregated by the level of precision ($p$ = 0.08 in EXO70; $p$ = 0.14 in EXO70, $\chi^2$ tests) – probably since the sample sizes become much smaller.[18]

***Figure 3.*** *Rate of efficient service provision, by treatment*




Note: All bars in the figure include 95% confidence intervals.

We also test Predictions 1-4 in the multivariate OLS regressions shown in Table 4.[19] The dependent variable in the regressions is whether the expert followed the signal. We first provide a parsimonious specification with only price vector, insurance, and the EXO70 treatment dummy as independent variables. We then add a specification that further includes the interaction term between insurance and treatment, as well as a third one that includes additional control variables (period, experts' demographics, risk attitudes, and the two social preference parameters $\lambda_D$ and $\lambda_A$).

[17] Differences in efficient provision rates across EXO100 and EXO70 are significant both under NI and FI ($p < 0.01$ for both comparisons, $\chi^2$ tests). These differences are significant under UT and EM price vectors ($p < 0.01$, $\chi^2$ tests), but not for OT vectors ($p$ = 0.18).
[18] Similarly, disaggregating by price vector, the comparison of efficient provision rates between NI and FI is significant only for UT price vectors ($p$ = 0.02, $\chi^2$ test).
[19] The regression results are robust to the use of Probit as the estimation method.

To test Prediction 4, in the last two columns we run the column (3) regressions separately for NI and FI. All regressions in this section include subject random effects and report standard errors clustered at the matching group level.

***Table 4.*** *Determinants of efficient service provision*

| | (1)<br>NI & FI | (2)<br>NI & FI | (3)<br>NI & FI | (4)<br>NI | (5)<br>FI |
|---|---|---|---|---|---|
| *EXO70* | $-0.063^{***}$ | $-0.066^{***}$ | $-0.066^{***}$ | $-0.071^{***}$ | $-0.060^{**}$ |
| | (0.019) | (0.021) | (0.022) | (0.025) | (0.026) |
| *Insurance* | $-0.043^{***}$ | $-0.045^{***}$ | $-0.049^{***}$ | | |
| | (0.012) | (0.012) | (0.013) | | |
| *UT price vector* | $0.116^{***}$ | $0.116^{***}$ | $0.121^{***}$ | $0.088^{***}$ | $0.154^{***}$ |
| | (0.017) | (0.017) | (0.019) | (0.024) | (0.026) |
| *OT price vector* | $-0.081^{***}$ | $-0.081^{***}$ | $-0.068^{***}$ | $-0.111^{***}$ | -0.029 |
| | (0.021) | (0.021) | (0.021) | (0.029) | (0.024) |
| *Insurance x EXO70* | | 0.004 | | | |
| | | (0.024) | | | |
| *Period* | | | $-0.002^{**}$ | -0.001 | $-0.004^{**}$ |
| | | | (0.001) | (0.001) | (0.002) |
| *Risk measure* | | | -0.007 | -0.002 | $-0.013^{*}$ |
| | | | (0.006) | (0.006) | (0.007) |
| $\lambda_D$ | | | 0.042 | 0.040 | 0.046 |
| | | | (0.032) | (0.032) | (0.041) |
| $\lambda_A$ | | | 0.017 | $0.060^{*}$ | -0.023 |
| | | | (0.025) | (0.034) | (0.027) |
| *Female* | | | 0.018 | 0.026 | 0.010 |
| | | | (0.025) | (0.028) | (0.026) |
| *Age* | | | 0.001 | 0.002 | 0.000 |
| | | | (0.003) | (0.004) | (0.004) |
| N | 4704 | 4704 | 3792 | 1896 | 1896 |

**Notes:** Dependent variable is *efficient service provision*, equal to 1 if the expert followed the received signal and 0 otherwise. The table presents estimates from OLS regressions with subject random effects. Standard errors are clustered at the matching group level and stated in parentheses. *EXO70* is equal to 1 for the EXO70 treatment. *Insurance* is equal to 1 if the consumer was insured in a particular period. *UT price vector* is equal to 1 if the price for the LQS is 60 and the price for the HQS is 80. *OT price vector* is equal to 1 if the price for the LQS is 60 and the price for the HQS is 120. The omitted benchmark is the EM vector with the price of 60 for LQS and of 100 for HQS. *Risk Measure* is constructed from responses to a survey question on a scale from 0 'fully risk averse' to 10 'fully risk seeking' and is available for participants in all but one session. $\lambda_D$ and $\lambda_A$ are elicited in the EET and range from -5/6 to 5/6, with higher values indicating stronger prosociality. These variables are reported for experts and are missing for 41 subjects, for whom choices in the online part of the experiment could not be matched to the lab part. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The regression results in the first three columns confirm Predictions 1-3. The negative effects of diagnostic uncertainty and insurance coverage on efficient service provision are captured by the statistically and economically significant coefficients for *EXO70* and *Insurance*. Diagnostic uncertainty decreases the likelihood of efficient service provision by over 6 percentage points and insurance decreases it by up to 5 percentage points. These are average effects for each dimension, while the interaction between the two dimensions is insignificant in column (2). The regressions also confirm the strong positive (negative) effect of UT (OT) price vectors on efficient service provision compared to the omitted category of EM prices, with effect sizes being around 7 to 8 percentage points for the OT vector and larger than 12 percentage points for the UT vector. All control variables are insignificant, with the exception of *Period*, suggesting a slight downward time trend. A test of Prediction 4 amounts to testing the joint significance of $\lambda_D$ and $\lambda_A$ in (4) and (5). The two prosociality measures have the predicted positive coefficient and are jointly significant under NI ($p = 0.02$, $\chi^2$ test), but they are jointly insignificant under FI ($p = 0.64$, $\chi^2$ test). Hence, the data provide only partial support for Prediction 4.

**Result 1 (Provision behavior):** *Predictions 1-3 are all supported by the experimental data. Experts are more likely to decide for the efficient service provision when diagnostic precision is higher and with the undertreatment price vector, and they are less likely to do so when insurance is in place and with the overtreatment price vector. There is only partial support for Prediction 4: Our measures of prosociality affect experts' provision behavior only in the absence of insurance coverage.*

### 5.2. Impact of Prices and Insurance on Investment in Diagnostic Precision (ENDO)

We now turn to Predictions 5 and 6 regarding investment in diagnostic precision by experts in ENDO. In this treatment the expert chooses between six different levels of diagnostic precision. The distribution of choices is shown in Table 5 (along with the costs in ECU for each choice). Overall (i.e., pooling ENDO-NI and ENDO-FI), a precision level of 80% is both the median value and the modal choice of experts. At this level, diagnostic precision costs are 3.6 ECU. By contrast, efficiency would prescribe to acquire the 100% precise signal at the cost of 10 ECU.

According to Prediction 5, experts should invest most in diagnostic precision with the UT price vector, an intermediate level with the EM price vector, and least with the OT price vector. This prediction is not supported by our data: Overall, experts invest slightly more tokens with the UT than with the EM price vector (3.80 compared to 3.56), but the difference is insignificant ($p = 0.403$, Mann-Whitney U test). Investment in precision is even higher with the OT (4.07) than with the EM price vector ($p < 0.01$, Mann-Whitney U test).

Prediction 6 states that insurance coverage for consumers leads to a reduction in experts' investment in diagnostic precision. Indeed, comparing the distribution of chosen precision between the third and fourth column of Table 5 reveals that experts choose significantly lower precision levels when insurance is in place ($p = 0.04$, $\chi^2$ test). The resulting precision levels in periods with and without insurance are 75.3% and 77.2%, respectively. Table 5 further reveals that a zero investment in precision is more frequent in the presence of insurance (20.7% vs. 16.1%, $p < 0.01$, $\chi^2$ test).

***Table 5.*** *Investment in diagnostic precision*

| Diagnostic precision (in %) | Cost (in ECU) | ENDO-NI | ENDO-FI | Pooled |
|---|---|---|---|---|
| 50 | 0 | 16.12 | 20.74 | 18.43 |
| 60 | 0.4 | 4.44 | 5.89 | 5.16 |
| 70 | 1.6 | 17.93 | 16.39 | 17.16 |
| 80 | 3.6 | 28.99 | 26.27 | 27.63 |
| 90 | 6.4 | 18.03 | 17.75 | 17.89 |
| 100 | 10 | 14.49 | 12.95 | 13.72 |

**Notes:** The table reports the relative frequencies (in %) with which the six different levels of diagnostic precision were chosen by experts.

The regressions in Table 6 provide further support for the effect of insurance on endogenously chosen diagnostic precision. The dependent variable in these regressions is the investment by experts into precision in ENDO, ranging from 0 to 10 ECU. The independent variables are the same as in the regressions of Table 4 (except for EXO70 and its interaction with insurance). The first two columns present results from ordered Probit regressions and the last two columns from OLS regressions. Regarding Predictions 5 and 6, the key things to note are the significantly negative coefficient on *Insurance* and the significantly positive coefficient for the OT price vector. Moreover, the significantly positive coefficients for the expert's $\lambda_D$ parameter shows that more prosocial experts in the domain of disadvantageous inequality invest more in a precise signal. This provides direct support for Prediction 7.[20]

**Result 2 (Investment in diagnostic precision):** *Prediction 5 is refuted by the data. Predictions 6 and 7 are confirmed: Insurance leads to a reduction in experts' investments and to lower precision, and more prosocial experts invest more in diagnostic precision.*

[20] The coefficient on $\lambda_A$ is also positive, but insignificant. The fact that Prediction 7 is more strongly borne out in the domain of disadvantageous inequality ($\lambda_D$) is not unexpected, given that experts generally earn substantially less than consumers in all treatments (see Table 3).

***Table 6.*** *Determinants of investment in diagnostic precision*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Insurance* | -0.133$^{**}$ | -0.148$^{**}$ | -0.288$^{**}$ | -0.327$^{*}$ |
| | (0.059) | (0.067) | (0.141) | (0.170) |
| *UT price vector* | 0.163 | 0.195 | 0.237 | 0.273 |
| | (0.115) | (0.120) | (0.275) | (0.309) |
| *OT price vector* | 0.183$^{***}$ | 0.186$^{***}$ | 0.508$^{***}$ | 0.525$^{***}$ |
| | (0.050) | (0.056) | (0.122) | (0.142) |
| *Period* | | -0.023$^{***}$ | | -0.046$^{***}$ |
| | | (0.006) | | (0.014) |
| *Risk measure* | | -0.027 | | -0.084 |
| | | (0.050) | | (0.120) |
| $\lambda_D$ | | 0.533$^{**}$ | | 1.672$^{***}$ |
| | | (0.240) | | (0.629) |
| $\lambda_A$ | | 0.265 | | 1.004 |
| | | (0.334) | | (0.840) |
| *Female* | | -0.138 | | -0.415 |
| | | (0.219) | | (0.571) |
| *Age* | | 0.025 | | 0.053 |
| | | (0.020) | | (0.046) |
| Constant | | | 3.703$^{***}$ | 3.055$^{**}$ |
| | | | (0.244) | (1.355) |
| N | 2208 | 1584 | 2208 | 1584 |

**Notes:** Dependent variable is the number of invested ECU in diagnostic precision, ranging from 0 to 10. The table presents subject random effects regressions, using ordered Probit in columns (1) and (2) and Ordinary Least Squares in columns (3) and (4). Standard errors are clustered at the matching group level and stated in parentheses. The independent variables are defined as in Table 3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### 5.3. Trading Decisions of Consumers

Rates of accepting to trade are generally very high, with a mean of 92.4% across all periods and treatments. In line with Prediction 8(a), we find that trade is most likely with the UT price vector, intermediate with the EM price vector, and lowest with the OT price vector.[21] This holds for all treatments. The differences between EM and OT price vectors are always significant ($p < 0.01$, $\chi^2$-tests), while the differences between UT and EM price vectors are not.

The effects of insurance on the willingness to trade confirm our Prediction 8(b). Under FI, trading rates are at 98% both in EXO and ENDO, while under NI they are 87% in EXO and 89% in EXO, with all differences significant at $p < 0.01$ ($\chi^2$-tests). Finally, also Prediction 8(c) is supported by the data. A higher diagnostic precision is associated with significantly higher trading rates (94.7% in the aggregate in EXO100 vs. 90% in EXO70, $p < 0.01$, $\chi^2$-test).

[21] In the (pooled) EXO treatments, the rates are 96.8%, 95%, and 85.5% for UT, EM, and OT price vectors respectively, and for ENDO the corresponding rates are 98%, 96.6%, and 86.8%.

The Probit regressions on willingness to trade shown in Table 7 report the results from two specifications for the exogenous treatments (differing in the number of control variables), followed by two specifications for treatment ENDO. These regressions provide support for the comparison between the OT and the EM price vector in the second part of Prediction 8(a), with consumers in all specifications being less likely to trade when prices reflect overtreatment incentives. There is support for the first part of Prediction 8(a), but only in the exogenous treatments, given the significant positive coefficients for the UT price vector in columns (1) and (2). Consumers are significantly more likely (by almost 10 percentage points) to trade on the market when they are insured, in the exogenous treatments as well as in ENDO, thus confirming Prediction 8(b). With respect to the effects of diagnostic uncertainty in the exogenous treatments, the significant coefficient for EXO70 indicates that consumers are about 4 percentage points less likely to trade when the expert receives an imprecise exogenous signal about his problem, thus confirming Prediction 8(c).

***Table 7.*** *Determinants of willingness to trade*

| | (1) | (2) | (4) | (5) |
|---|---|---|---|---|
| | EXO70 & EXO100 | EXO70 & EXO100 | ENDO | ENDO |
| *EXO70* | -0.041*** | -0.043*** | | |
| | (0.010) | (0.011) | | |
| *Insurance* | 0.092*** | 0.085*** | 0.072*** | 0.057*** |
| | (0.010) | (0.017) | (0.016) | (0.015) |
| *UT price vector* | 0.017** | 0.017** | 0.014 | 0.005 |
| | (0.008) | (0.008) | (0.009) | (0.009) |
| *OT price vector* | -0.075*** | -0.074*** | -0.080*** | -0.075*** |
| | (0.012) | (0.012) | (0.015) | (0.016) |
| *Insurance x EXO70* | | 0.012 | | |
| | | (0.021) | | |
| *Period* | | 0.002*** | | 0.001*** |
| | | (0.001) | | (0.001) |
| *Risk measure* | | 0.004* | | 0.006 |
| | | (0.002) | | (0.004) |
| $\lambda_D$ | | 0.012 | | -0.012 |
| | | (0.014) | | (0.013) |
| $\lambda_A$ | | 0.022 | | 0.050*** |
| | | (0.015) | | (0.016) |
| *Female* | | -0.024** | | 0.012 |
| | | (0.010) | | (0.012) |
| *Age* | | 0.000 | | 0.004* |
| | | (0.001) | | (0.002) |
| N | 4704 | 3936 | 2208 | 1608 |

Notes: Dependent variable is *Willingness to Trade*, equal to 1 if the consumer decided to trade and 0 otherwise. The table presents marginal effects estimates from Probit regressions with subject random effects. Standard errors are clustered at the matching group level and stated in parentheses. The independent variables are defined as in the notes to Table 4. * p < 0.10, ** p < 0.05, *** p < 0.01.

**Result 3 (willingness to trade):** *Consumers' willingness to trade is higher when insurance is in place, regardless of whether diagnostic precision is exogenous or not. In the exogenous case, a higher precision also increases the willingness to trade. Trade is less likely with the overtreatment than with the equal markup price vector. Overall, the data support Predictions 8(b) and 8(c) fully, and partly support Prediction 8(a).*

### 5.4. Market Efficiency

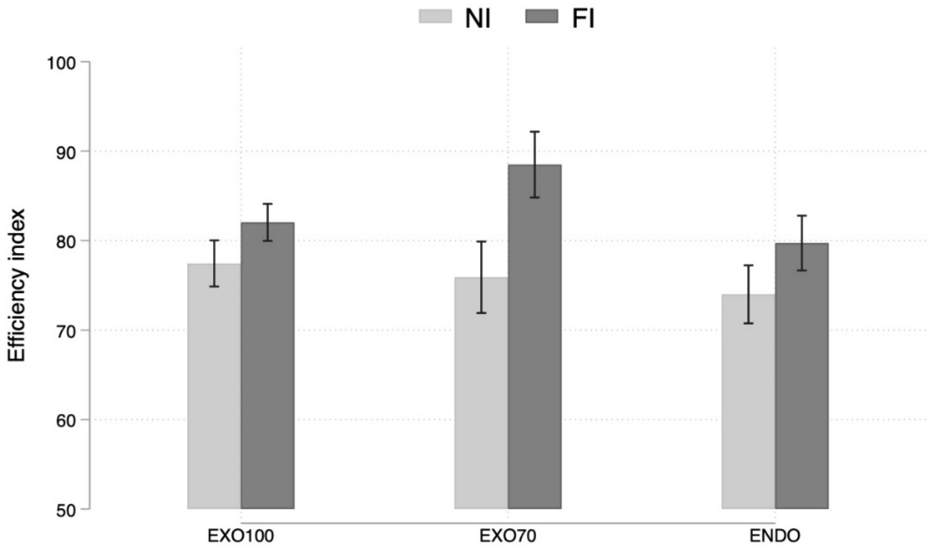
As a final part of our results section, we examine what the behavior of experts and consumers implies for market efficiency. The efficiency index used in this analysis measures (in %) which fraction of the highest possible efficiency gain is achieved in an expert-consumer interaction. The highest possible efficiency gain is the difference between the *first-best joint payoff* and the *minimal joint payoff*. In the EXO treatments the first-best joint payoff is achieved if the consumer trades on the market and the expert implements Strategy C, while in the ENDO treatments it is achieved if the consumer trades and the expert acquires the fully informative signal and follows the signal. In all treatments the minimal joint payoff is achieved if the consumer refuses interaction on the market.[22] The efficiency index is then calculated as follows: *Efficiency Index = (actual joint payoff – minimal joint payoff) / (first-best joint payoff – minimal joint payoff).*

Figure 4 shows efficiency levels across treatments. The figure reveals that efficiency is always higher under full insurance (dark bars) than under no insurance (light bars). The difference is statistically significant for all three treatments pooled ($p < 0.01$, Wilcoxon signed-ranks test) and in the two exogenous treatments separately ($p < 0.01$ in EXO70, $p < 0.05$ in EXO100, Wilcoxon signed-ranks tests), while it is insignificant in ENDO ($p = 0.12$).[23]

[22] The first-best joint payoff equals $v - h\overline{c} - (1-h)\underline{c} - D(1) = 150 - 0.4 * 60 - 0.6 * 20 - 10 = 104$ in treatments EXO100 and ENDO, and $[1 - h(1-\sigma)]v - (1 - h - \sigma + 2h\sigma)\overline{c} - (h + \sigma - 2h\sigma)\underline{c} - D(\sigma) = 0.88 * 150 - 0.46 * 60 - 0.54 * 20 - 1.6 = 92$ in EXO70. The minimal joint payoff is 30 (the sum of the two outside payoffs in the case of no trade) in all treatments.

[23] Comparing efficiency across treatments is less meaningful, given the way our efficiency index is constructed. For completeness, we note that the efficiency index does not vary significantly between the two exogenous treatments, and the only significant difference is between EXO70 and ENDO ($p < 0.05$, Mann-Whitney test).

***Figure 4.*** *Efficiency rates by treatment and insurance*




**Note:** All bars in the figure include 95% confidence intervals.

Table 8 presents estimates from linear regressions with the efficiency index as dependent variable. In these regressions, each consumer-expert interaction is one data point, since efficiency is measured at the market interaction level. We separate between cases with exogenous (columns 1 and 2) and endogenous (column 3) diagnostic precision. This distinction allows us to cleanly identify the effects of diagnostic precision on efficiency, but also to include the chosen level of investment in column (3).

In line with the non-parametric test results, insurance has a sizeable and significant positive impact on the efficiency index (ranging from 5 to 9 percentage points) in the exogenous as well as in the endogenous treatments. This effect is stronger in the presence of diagnostic uncertainty, as evinced by the positive and significant interaction term in (2). This analysis suggests that the drop in efficient service provision as a result of insurance documented in section 5.1 is outweighed by the increase in the frequency of trade documented in section 5.3, leading to a beneficial net impact of insurance coverage on efficiency.

In treatment ENDO, experts' investments into diagnostic precision have a highly significant positive effect on efficiency. The intuition here is that experts who have achieved a higher precision are more likely to follow the signal and, thus, more likely to provide the correct quality. We further document an efficiency-diminishing effect of OT price vectors, which is of considerable magnitude. This finding is aligned with the way prices affect the behavior of experts in the exogenous treatments (see Prediction 1 and Result 1), with OT price vectors yielding lower rates of efficient service provision than EM price vectors.

***Table 8.*** *Regressions on market efficiency*

| Treatment(s) | (1)<br>EXO100 & EXO70 | (2)<br>EXO100 & EXO70 | (3)<br>ENDO |
|---|---|---|---|
| *Insurance* | 0.086*** | 0.048*** | 0.062** |
| | (0.018) | (0.018) | (0.029) |
| *EXO70* | 0.025 | -0.015 | |
| | (0.017) | (0.029) | |
| *UT price vector* | 0.020 | 0.020 | -0.020 |
| | (0.018) | (0.018) | (0.032) |
| *OT price vector* | -0.117*** | -0.116*** | -0.076*** |
| | (0.018) | (0.018) | (0.022) |
| *Insurance x EXO70* | | 0.078** | |
| | | (0.035) | |
| *Investment* | | | 0.019*** |
| | | | (0.004) |
| *Period* | 0.003*** | 0.003*** | 0.004** |
| | (0.001) | (0.001) | (0.002) |
| constant | 0.745*** | 0.765*** | 0.650*** |
| | (0.025) | (0.026) | (0.031) |
| N | 4704 | 4704 | 2208 |

**Notes:** Dependent variable: *Efficiency Index*. The table presents random effects OLS regressions. Standard errors are clustered at the matching group level and stated in parentheses. The independent variables are defined as in the notes to Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## 6. Concluding Remarks

In a laboratory experiment conducted with 576 participants we test a series of predictions based on a theoretical paper by Balafoutas et al. (2023) that features four important and common features of credence goods markets, namely (i) diagnostic uncertainty in the diagnosis of expert sellers, (ii) insurance coverage of consumers, (iii) malpractice payments, and (iv) the possibility that some experts display consumer-regarding preferences. Our aim has been to offer key insights into how diagnostic uncertainty, an important but hitherto underexplored aspect of credence goods markets, affects outcomes in such markets, but also into factors that shape the willingness of expert sellers to invest in a higher diagnostic precision.

The experimental findings largely confirm our predictions and reveal important effects of diagnostic uncertainty and insurance and their interaction – effects that the previous literature could not uncover. For the parameter constellations used in the experiment, for which efficiency requires expert sellers to follow the signal they receive about a consumer's needs, lower diagnostic precision leads to less efficient provision. Insurance has the same predicted effect of reducing efficient service provision, and in addition it leads to a reduction in experts' investment in diagnosis and therefore to lower precision (when this is endogenous). Another factor that is shown to affect investments in diagnostic precision is the strength of consumer-regarding motivation on the part of the sellers. In line with our hypotheses, the rates of efficient service provision are highest with undertreatment price vectors and lowest with overtreatment vectors. Finally, the willingness of consumers to trade on the market increases with diagnostic precision and insurance, implying that higher precision as well as insurance increase efficiency.

We hope that our findings – although we would not want to draw too strong conclusions from a laboratory experiment – can provide some evidence-based input into the policy debate about the organization and potential regulation of credence goods markets. For instance, our finding that higher diagnostic precision increases market efficiency through reducing incentives for over- or undertreatment suggests that technological progress to improve diagnostic precision is socially welcome from an efficiency point of view. Seen from this angle, it is good news when advances in medical science make diagnoses less error-prone (Gottschalk et al., 2020) or when websites help consumers to identify their needs (Kerschbamer et al., 2023). Diagnostic precision is also linked to insurance coverage, but this relationship has never been investigated before. Importantly, insurance coverage provides negative incentives for diagnostic precision, implying that regulatory policies that introduce a requirement to buy insurance may have unintended side effects on experts' effort provision to diagnose consumers' problems properly. For this reason, an important avenue for future research may be to look more deeply into what happens when consumers can only get partial insurance – meaning that they have to pay deductibles even when being insured – or when they can endogenously choose the extent of insurance. It would also be interesting to study whether markets may split up in consumers who ask for insurance while others remain (voluntarily) uninsured, and how experts would respond with their diagnosis effort and tailor their offers to both types of consumers.

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## Appendix A. Parameters of the EET and translation of EET results in parameter values

***Parameters in the Equality Equivalence Test***

**Advantageous Inequality Block**

| LEFT | | RIGHT | |
|---|---|---|---|
| decision maker's payoff | passive person's payoff | decision maker's payoff | passive person's payoff |
| 8 ECU | 7 ECU | 10 ECU | 10 ECU |
| 9 ECU | 7 ECU | 10 ECU | 10 ECU |
| 10 ECU | 7 ECU | 10 ECU | 10 ECU |
| 11 ECU | 7 ECU | 10 ECU | 10 ECU |
| 12 ECU | 7 ECU | 10 ECU | 10 ECU |

**Disadvantageous Inequality Block**

| LEFT | | RIGHT | |
|---|---|---|---|
| decision maker's payoff | passive person's payoff | decision maker's payoff | passive person's payoff |
| 8 ECU | 13 ECU | 10 ECU | 10 ECU |
| 9 ECU | 13 ECU | 10 ECU | 10 ECU |
| 10 ECU | 13 ECU | 10 ECU | 10 ECU |
| 11 ECU | 13 ECU | 10 ECU | 10 ECU |
| 12 ECU | 13 ECU | 10 ECU | 10 ECU |

**Note:** Decision makers had to indicate, for each of the ten decision situations, whether they wanted to implement the LEFT or the RIGHT allocation

## ***Translation of Decisions in the Equality Equivalence Test into λ Values***

Denote the own material payoff by *m* and the other's payoff by *o*. Suppose subjects in the lab decide in line with the utility function $u(m,o) = m + \lambda o$, as assumed for experts in our model. What can we infer about λ from their choices in the EET?

**Advantageous Inequality Block (Y-List)**

| subject chooses LEFT for the first time in row | inference regarding $\lambda_A$ | attributed $\lambda_A$ |
|---|---|---|
| 1 (always left) | $\lambda_A \leq -2/3$ | $\lambda_A = -5/6$ |
| 2 | $-2/3 \leq \lambda_A \leq -1/3$ | $\lambda_A = -3/6$ |
| 3 | $-1/3 \leq \lambda_A \leq 0$ | $\lambda_A = -1/6$ |
| 4 | $0 \leq \lambda_A \leq 1/3$ | $\lambda_A = 1/6$ |
| 5 | $1/3 \leq \lambda_A \leq 2/3$ | $\lambda_A = 3/6$ |
| never (always right) | $2/3 \leq \lambda_A$ | $\lambda_A = 5/6$ |

**Disadvantageous Inequality Block (X-List)**

| subject chooses LEFT for the first time in row | inference regarding $\lambda_D$ | attributed $\lambda_D$ |
|---|---|---|
| 1 (always left) | $2/3 \leq \lambda_D$ | $\lambda_D = 5/6$ |
| 2 | $1/3 \leq \lambda_D \leq 2/3$ | $\lambda_D = 3/6$ |
| 3 | $0 \leq \lambda_D \leq 1/3$ | $\lambda_D = 1/6$ |
| 4 | $-1/3 \leq \lambda_D \leq 0$ | $\lambda_D = -1/6$ |
| 5 | $-2/3 \leq \lambda_D \leq -1/3$ | $\lambda_D = -3/6$ |
| never (always right) | $\lambda_D \leq -2/3$ | $\lambda_D = -5/6$ |

## Appendix B. Experimental Instructions

*The following sections contain the instructions translated from German, which were used in the online and lab part of the experiment. We read out all instructions out loud in the lab. If instructions were different between treatments, this is indicated by squared brackets, including the respective treatment condition and the according text in italic letters. To match the observations from the online and the lab part, participants created a unique in the online part and had to state this ID at the beginning of the lab part.*

### B.1. Instructions for Online Part

The first part of the experiment will be conducted online and consists of 10 decisions. In each of these 10 decisions, the computer randomly assigns another participant to you. In the following, we will call this participant "Your Passive Person". You will never learn the identity of your passive person. You will see below why we call this person a "passive person".

We state the payoffs in ECU (experimental currency units).
The exchange rate is 5 ECU = 1 Euro

Each of your 10 choices is a choice between the LEFT and the RIGHT option. Each option has consequences for your payoff and the payoff of your passive person.

Example:

You will be asked if you prefer to choose the option LEFT, where you will receive 8 ECU and your passive person 13 ECU, or option RIGHT, where you will receive 10 ECU. Your passive person will also receive 10 ECU. You have to choose one of the two options by clicking on the corresponding circle.

This decision problem would be presented on the screen as follows:

**Your decision**

**Option 'Left'** **Option 'Right'**

| *Your Payoff* | *Payoff passive person* | | | *Your Payoff* | *Payoff passive person* |
|---|---|---|---|---|---|
| 8,00 ECU | 13,00 ECU | O | O | 10,00 ECU | 10,00 ECU |

You have to make a total of 10 decisions (5 are shown per screen). Your total earnings from this part are determined as follows:

**Payout as Active Person:** In the end, one out of the 10 decision-making situations is selected individually and randomly for each participant, and the option chosen in this decision situation is then actually paid out. E.g., if you have chosen the decision situation described above and you have decided on the option RIGHT in this decision situation, you would receive 10 ECU as an active person. In contrast, your passive person would receive 10 ECU as a passive person.

**Payout as Passive Person:** Just as your Passive Person receives ECU from your decision without doing anything, you receive ECU from another participant without doing anything. This means you are the passive person for this other participant. It is assured that you will not be redeemed twice as an active and passive person. That is, if person X is your passive person, then you are certainly not the passive person of person X.

You will see 5 of all 10 decisions on one screen. You can make corrections to your choices as long as you have not clicked "Next".

After the 10 decisions, this part of the experiment ends. Which of your 10 decisions is relevant for your payoff and how much you have earned, you will get to know in the EconLab, when you participate in the lab part. Also, this online part will be paid at the EconLab in cash.

## B.1. Instructions for Lab Part

### <u>Instructions</u>

Thank you for your participation in the experiment. Please do not talk to other participants until the end of the experiment.

In this experiment, the payoffs are stated in ECU (experimental currency units).
The exchange rate is 80 ECU = 1 €.

Different roles:

There are two roles in the experiment: client and expert. At the beginning of the experiment, you will be randomly assigned one of these roles and keep that role for the entire experiment, which means for all periods. At the first decision screen (period 1 of 24), you will see your role.

In each period, one expert is randomly assigned to one client (and vice versa). It is ensured in each period that the same client-expert pair is never formed in two consecutive periods. This means that a client always interacts with an expert, and you will randomly get a partner in each period.

### <u>24 Periods</u>

This experiment consists of 24 periods, each with the same sequence of decisions described below.

Suppose you have been assigned a client's role. In that case, you have a big problem with a probability of 40% and a small problem with a probability of 60%. As a client, you will never be informed about the problem you actually have. As a client, you can decide if you enter the market, which means you want to interact with the expert randomly assigned to you. By entering the market, your problem may be solved by the expert. If your problem is solved, you will receive 150 ECU in this period. If your problem is not solved, the expert has to pay you a compensation of 50 ECU (more on this below).

*[EXO100]*

*- If you have been assigned the role of an expert, you will receive in each period a signal about what problem your client (randomly matched with you) has. This signal is 100% accurate. That is, if e.g., the client has a small problem, then, with 100% probability, you get the signal that the problem is small; and similar to the big problem. However, this information costs 10 ECU. These costs will be deducted automatically in each period.*

*[EXO70]*

*- If you have been assigned the role of an expert, you will receive in each period a signal about what problem your client (randomly matched with you) has. This signal is 70% accurate. If e.g., the client has a small problem, then, with 70% probability, you get the signal that the problem is small; and similar to the big problem. However, this information costs 1.6 ECU. These costs will be deducted automatically in each period.*

*[ENDO]*

*If you have been assigned an expert's role, you will receive a signal each period about the client's problem randomly. As an expert, you decide on the precision of the received signal. The costs associated with each precision level are given in the following table:*

| *Precision of the signal* | *Costs* |
|---|---|
| *50%* | *0 ECU* |
| *60%* | *0.4 ECU* |
| *70%* | *1.6 ECU* |
| *80%* | *3.6 ECU* |
| *90%* | *6.4 ECU* |
| *100%* | *10 ECU* |

*For example, suppose you choose a 70% precise signal. In that case, you pay 1.6 ECU and get a signal that identifies the problem correctly with a 70% probability. If you select a 50% precision, you will not be charged. However, your signal is not informative (because it identifies the actual problem with the same probability as right or wrong).*

As an expert, your job is to treat the client. You can choose between a low quality treatment and a high quality treatment. The low quality treatment only solves the small problem of the client. The high quality treatment solves both the small and the big problem. You always have to pay ECU 20 for a low quality treatment and 60 ECU for a high quality treatment. If your treatment has not solved the client's problem, then as an expert, you have to pay a compensation fee of 50 ECU.

For the treatment of low quality, you will receive from the client a price of 60 ECU. For high quality treatment, the price is either 80 ECU, 100 ECU, or 120 ECU: this price varies over periods, and you will find out the respective price at the beginning of each period.

- Treatment can only be carried out if the client has decided to enter the market. If the client chooses not to enter the market, that is, if he /she decides not to interact with the expert, both client and expert receive a payoff of 15 ECU in this period.

## Overview of the Decisions of one Period

Therefore, each period consists of decisions of the expert and the client, which are made simultaneously and independently of each other.

| Client: | Expert: |
|---|---|
| The client decides if he/she wants to enter the market. | *[ENDO]*<br>*1. The expert decides on the signal precision.*<br>*2. The expert receives the signal about the client's problem and decides if he/she wants to use the high or low quality treatment.*<br>*[EXO100] and [EXO70]*<br>*The expert receives the signal about the client's problem and decides whether he /she wants to implement the high or low quality treatment.* |

Only after both made their decisions it is announced whether the client has entered the market or not. If the client has not entered, the expert's decisions are irrelevant. In summary, this leads to the following payoffs:

## Payoffs

CLIENT DOES NOT ENTER THE MARKET: both the client and the expert receive 15 ECU.

CLIENT ENTERS THE MARKET:

**Client:**

If the problem was solved: 150 ECU minus the treatment price

If the problem was NOT solved: 50 ECU minus the treatment price

**Expert:**

*[EXO70] If the problem was solved: treatment price minus treatment cost minus 1,6 (costs diagnostic precision 70%)*

*[EXO100] If the problem was solved: treatment price minus treatment cost minus 10 (costs diagnostic precision 100%)*

*[EXO70] If the problem was not solved: treatment price minus treatment cost minus 50 ECU (compensation) minus 1,6 (costs diagnostic precision 70%)*

*[EXO100] If the problem was not solved: treatment price minus treatment cost minus 50 ECU (compensation) minus 10 (costs diagnostic precision 100%)*

*[ENDO]*

*If the problem was solved: treatment price minus treatment cost minus the cost for the selected signal precision level*

*If the problem was not solved: treatment price minus treatment cost minus 50 ECU (compensation) minus cost for the selected signal precision level*

## <u>Insurance</u>

Please note that there are two possible market situations in each period: either the client is insured or not. You play a total of 12 periods with and 12 periods without insurance, and you will see at the beginning of each period on the screen if the particular period is a period with insurance or not.

In a period without insurance, the situation is the same as previously described. In a period with insurance, the client is insured. This means that at the beginning of such a period, the client pays an insurance premium of 80 ECU (deducted automatically, even if the client does not enter the market). In return, the price for the client's treatment is covered by the insurance. All decisions taken by the client and the expert remain the same as in periods without insurance. The payoffs of the two parties in periods with insurance are as follows:

Payoffs in periods with insurance:

Client:

CLIENT DOES NOT ENTER THE MARKET: 15 ECU minus 80 ECU (insurance premium) = -65 ECU

CLIENT ENTERS THE MARKET:

If the problem has been solved: 150 ECU minus 80 ECU (insurance premium) = 70 ECU

If the problem was NOT solved: 50 ECU minus 80 ECU (insurance premium) = -30 ECU

Expert:

For the expert, the payoff does not change. It is calculated as in periods without insurance.

## Information and Feedback

In each period, the expert and the client get to know whether the client is insured in this period and the prices for the low and high quality. The expert also receives the signal about the problem of the client. After the second period, you can see the results of all past periods at the bottom of your screen.

## Total Payoff

At the beginning of the experiment, you will receive an endowment of 80 ECU. From this endowment, you can also cover possible losses in individual periods. Profits from other periods also compensate for losses.

For the final payoff, each period's endowment and the payoffs are added together and paid in cash at the end of the experiment, using the exchange rate 80 ECU = 1 €. Also, you will receive your payoff from the online part.