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Expert Qualification in Markets for Expert Services: A Sisyphean Task?

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Abstract

Moral hazard in expert diagnoses is more complicated in credence goods markets because ex-post verification of service optimality is usually not possible. We provide an experimental framework to investigate expert and consumer behavior as well as market efficiency in a setting in which experts need to invest in costly but unobservable effort to identify consumer problems and consumers are able to visit multiple experts for diagnosis. We introduce heterogeneously-qualified experts, varying in their necessary effort to diagnose consumers. We examine how subjects react to expert qualification and the introduction of price competition. We find that our baseline market is more efficient and qualification is not necessarily the Sisyphean task, as theory predicted. Nevertheless, we observe high skilled experts investing significantly less effort in diagnoses than their low skilled counterparts. Qualifying experts increases efficiency with fixed prices but remains almost without influence in markets with price competition. Introducing price competition does not lead to the predicted market breakdown, but rather has negative effects on market efficiency. In sum, whether expert qualification should be pursued in credence goods markets depends on the market composition and existing institutions.

Keywords: credence goods; expert market; laboratory experiment; expert qualification; second opinions; price competition

JEL: D12; D82; C91

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1 Introduction

Markets for credence goods - commonly referred to as markets for expert services - are characterized by information asymmetries between consumers and experts. Consumers are only aware of having a problem but cannot determine the exact kind and service that would be optimal for a solution. They have to contact experts for advice, who are typically better informed and can both diagnose consumer problems and carry out necessary services. The most common examples are given by markets for health care, automobile repair, legal and financial services, as well as home improvements. The exception for credence goods - in contrast to search and experience goods - is given by information asymmetries even persisting after trade has taken place, implying that consumers cannot determine whether the received service was optimal even if their problem has been solved (Darby, Karni, 1973). These information asymmetries lead to incentive problems which can result in welfare losses and potential market breakdowns (Akerlof, 1970). According to the literature, we assume that these problems remain unaffected or are even amplified by expert qualification and price competition, branding them as Sisyphean tasks (Pesendorfer, Wolinsky, 2003; Schneider, Bizer, 2017). According to the everyday practiced and demanded qualification in professional life as well as the immanent importance of credence goods markets (Bester, Dahm, 2017; Kerschbamer, Sutter, 2017) and rare empirical evidence, an analysis of potential side effects of expert qualification appears immanent.

The main body of literature on credence goods focuses on exploitation by experts providing suboptimal treatments enabled by their sole ability to identify consumer problems, while missing out the moral hazard problem in the diagnosis stage. It is mainly assumed that experts are able to identify consumer problems with certainty at no costs, e.g. (Wolinsky, 1993; Dulleck, Kerschbamer, 2006; Dulleck et al., 2011; Hyndman, Ozerturk, 2011; Mimra et al., 2016a; Schneider et al., 2016). However, (Akerlof, 1970) has already highlighted in his 'market for lemons' that sellers need to invest some effort to identify the quality of an owned car, e.g. by possessing and using it. In case experts do not invest sufficient effort in their diagnosis, this endangers consumers being undertreated. There is a moral hazard problem because experts' invested effort is not observable for consumers. Imagine that a physician needs to diagnose the type and severity of a patient's illness. He has to decide how much time and which diagnostic tools or procedures he wants to apply. While the patient may have some indication about the physician's intentions according to his conduct, she will struggle to identify whether the invested effort is appropriate for a corresponding diagnosis, given her individual situation and the physician's abilities and attributes. Trying to solve this dilemma by allowing patients to visit multiple physicians for diagnosis - e.g. (Pesendorfer, Wolinsky, 2003; Mimra et al., 2016b) - the problem prevails for two factors: first, the physician's invested effort is not observable to its full extent, e.g. the patient cannot identify how much time their physician actually spends on interpreting results after examination; second, even if effort were perfectly observable, the patient could not estimate whether the invested amount is appropriate to diagnose her problem sufficiently (Emons, 2001). She could only compare the invested amount of different physicians and evaluate the likely quality of diagnoses accordingly. However, this would not enable her to determine neither the optimal nor the necessary amount of effort to identify her problem. Regarding the information asymmetry, the optimal amount of effort for a diagnosis remains unknown to consumers even with multiple visits. This might be reinforced by physicians not being homogeneous, e.g. regarding their social preferences (Kerschbamer et al., 2017), diagnostic ability or their capacities, which makes the optimal amount of effort to diagnose a problem vary across physicians (Emons, 2001; Schneider, Bizer, 2017). Furthermore, additional qualification seems also not appropriate to solve the dilemma but is rather a Sisyphean task. We suspect that more qualified experts will reduce their effort in diagnosis, as they rely on their additional expertise and maximize their own welfare by reducing their investments. The results from Schneider (2012) in a field experiment with car mechanics point in the same direction, as he cannot identify an influence of age or acquiring a certification on the repair quality. Assuming that qualification is costly for society, qualification and certification programs might be in sum a waste of resources.

With experts' moral hazard problem in diagnosis, they might have incentives to under-invest for maximizing their own welfare. In a model where experts have restricted capacities, (Emons, 2001) show that full observability leads to an efficient outcome but market breakdowns otherwise. However, his results crucially depend on the absence of variable costs once capacity is chosen by experts. By contrast, in a market where consumers can visit multiple experts who have to invest in costly but unobservable diagnostic effort to identify consumer problems, Pesendorfer, Wolinsky (2003) show that welfare-maximizing states need additional institutions, i.e. fixed prices. Dulleck, Kerschbamer (2009) investigate a two-sided incentive problem when experts have a moral hazard problem in diagnosis and consumers can free-ride on this information by buying the required service from a discounter. They show that contingent diagnostic fees - i.e. reducing diagnostic costs in case the service is bought from the same expert - can solve the dilemma. Bonroy et al. (2013) show that experts' willingness to invest in costly diagnosis decreases with risk averse consumers but can be fixed by liability clause. However, all of these studies do not cover the topic of heterogeneously qualified experts in the market. In Schneider, Bizer (2017), we extend the framework of Pesendorfer, Wolinsky (2003) by introducing heterogeneously-qualified experts in their ability to diagnose consumer problems. We find that in case the share of high-skilled experts in the market is sufficiently high second-best equilibria are possible even with flexible prices and do not need additional institutions.

To our best knowledge, we are the first to introduce an experimental design to investigate experts' moral hazard problem from costly but unobservable diagnostic effort in a market for credence goods. Our main focus lies on how a varying share of high-skilled experts - who need to invest less effort to diagnose consumers (Brush et al., 2017; Norman et al., 2007) - and price competition affect economic outcome. We are particularly interested in the effect on experts' investments in diagnosis, consumers' willingness to contract and overall market efficiency. With experts' invested effort being unobservable to consumers, experts might have a financial incentive to under-treat consumers in diagnosis. For simplification, we assume that experts have the choice to invest either high or low effort in their diagnosis. With high effort, all experts unanimously provide a correct diagnosis. We further assume that experts are either high or low skilled, with high-skilled experts having some positive probability to provide a correct diagnosis even with low effort, while low-skilled experts will strictly provide wrong diagnoses in this case.

Our experiment builds closely on the designs of Dulleck et al. (2011), Mimra et al. (2016b) and Mimra et al. (2016a). However, rather than restricting possible services to only two levels - as in common credence goods model based on Wolinsky (1993) - we allow for a broader range. Additionally, by letting consumers search for matching opinions, we allow them to verify received recommendations endogenously. Outlined by Schneider, Bizer (2017), such a game has multiple equilibria. Besides the pure strategy degenerate equilibrium with consumers leaving the market without any action and no trade taking place, mixed strategy non-degenerate equilibria are possible in which consumers search for matching opinions and experts invest in high effort, both with some positive probability. To investigate how varying shares of high-skilled experts as well as price competition affect economic outcome, we use a classic 2x2 design. Notice that we keep the advantage of high-skilled experts in providing a correct recommendation constant by having a 50% probability of providing a correct diagnosis even with low effort. Consequently, we focus on the effects of different market compositions and their interactions with competition. In *Low* treatments we implement a relatively low share of high-skilled experts in contrast to a relatively high share in *High* treatments. Moreover, in *Fix* treatments, the price for diagnosis and service is given while in *Flex* treatments, this can be chosen freely by experts in each period.

We find experts adapting their investment decisions to their individual skills, although qualification is not necessarily a Sisyphean task. It appears that markets for credence goods with experts having a moral hazard problem in providing truthful diagnoses are more efficient than theory predicts. Experts invest on average more in their diagnosis, which increases the probability of consumers to get having problems identified correctly. As expected, high-skilled experts invest significantly less in their diagnoses than low-skilled experts, while both types invest more than their best response would be. However, consumers act quite risk averse. They seldom buy after a single diagnosis, frequently leave the market without any action and predominately opting for confirming diagnoses with other diagnoses before buying a service. While this causes higher transaction costs with more visited experts and a welfare loss on the one side, experts' high-effort investments and consumers' frequent verification lead to a much smaller proportion of wrong services than we expected. This overcompensates welfare losses from higher transaction costs and leads to a significantly higher market efficiency than predicted. By increasing the share of high-skilled experts in the market - to which we refer as expert qualification - market efficiency increases with fixed prices but appears to remain unaffected or even decline with price competition. In both cases, consumers act more rationally and leave less often without any action, which might be an indication of increased trust. However, according to high-skilled experts investing comparable less effort, this only weakly increases the probability of a correct diagnosis by expert qualification and only in a market without price competition. Looking at the effect of price competition in a high- or low-qualified market - i.e. with a high or a low share of high-skilled experts - the influence seems to be positive in a low-qualified market but rather negative in a high-qualified one. In a low-qualified market, while experts invest less effort and the probability of a correct signals decreases, consumers appear more trusting in term

of buying more often after only one diagnosis. This increases the market efficiency, albeit not significantly. In a high-qualified market, the effect of price competition reduces market efficiency with significantly fewer solved problems and more wrong services, even while consumers appear to act less risk averse. Across all treatments, consumers' risk aversion as well as experts' general over-investments with fixed prices prevail. By letting experts set prices on their own, we observe an increase in diagnosis prices and a decrease in service prices compared with fixed prices. Again, experts do not act according to their best response with high-skilled experts investing too much and low-skilled experts investing too little effort. By contrast, consumers would be expected not to participate in markets with average diagnosis prices above their critical threshold for positive expected payoff, which is crossed with flexible prices. However, as already mentioned, they appear to act less risk averse in such markets, which we explain by the perceived higher degree of freedom that experts have by setting prices freely, thus increasing consumers' trust as they might interpret this as higher attachments to ones duties.
The remainder of the paper is structured as follows. Section two reviews the related literature, before section three presents our experimental design. Section four offers a summary of the underlying model and states our hypothesis. Section five details our results and section six concludes.

2 Related Literature

In this section, we will review the most relevant literature. According to the information asymmetry, consumers need to contact experts for advice. In the literature for Judge-Adviser Systems (JAS), in general a judge (consumer) makes decisions based on formerly-acquired information from an adviser (expert) (Bonaccio, Dalal, 2006). By applying this scheme to our setup, two factors appear decisive: (1) what affects consumers' decisions whether to follow experts' messages, and (2) what affects experts' degree of sincerity in communication with the consumer. Previous research indicates that consumers adjust their willingness to follow advice to the type of source and its identifiable characteristics (Bonaccio, Dalal, 2006; Eckerd, Hill, 2012; Mortimer, Pressey, 2013; Schotter, 2003; White, 2005), thereby discounting experts' advice to different degrees, which is decisively influenced by whether advice has been liable to costs and when it was paid (Angelova, Regner, 2013; Gino, 2008). In general, consumers react by higher discounting rates when experts' interests are divergent from their own and if advice is imposed on them rather than solicited, seemingly whereby more degrees of freedom increase trust. The way in which advice is given also matters with most following in face-to-face situations (Bonaccio, Dalal, 2006). Regarding experts' willingness for sincere communication, Crawford, Sobel (1982) show that noisy signaling prevails until interests perfectly coincide. Rode (2010) indicates that experts' propensity to tell the truth is thus independent of the competitive context. By contrast, Sakamoto et al. (2013) show experimentally that experts are sensitive to context, i.e. to the likelihood of detection and whether a situation is framed as a potential win or loss. Angelova, Regner (2013) find that the frequency of truthful advice can be increased by payments in general but particularly with voluntary payments to advisers. Instead of purely objective considerations, consumers seem to rely on heuristics and subjective measurements concerning whether to trust experts.

While consumers appear to respond to experts' identifiable characteristics, is it questionable whether they are actually able to distinguish experts of different kinds in markets for credence goods. In Schneider, Bizer (2017) we describe that in such markets consumers should easily identify someone as being an expert because they usually act in regulated markets with entry barriers. However, determining an expert's actual level of skill is rather complicated. In most cases, a consumer is not aware of an expert's individual talent, years of experience, additional training or specializations. The literature assumes that in markets for credence goods, consumers cannot differentiate between experts of a different kind (Emons, 2001; Pesendorfer, Wolinsky, 2003; Feser, Runst, 2015). Consequently, consumers cannot adapt their strategy to individual experts but have to choose a uniform procedure. In a model with second opinions and price competition, Pesendorfer, Wolinsky (2003) let experts' skill levels directly determine their ability to recommend an appropriate treatment. By contrast, in Schneider, Bizer (2017) we argue that the assumption of low skilled experts unanimously providing low quality in diagnosis does not capture real life circumstances. Thereby, market efficiency should not increase with more qualified experts in a market, as high-skilled experts are expected to reduce their effort in diagnosis to balance the overall probability of consumers receiving a correct diagnosis. However, suitable results from (field) experiments to verify these theoretical results are missing to date.

The introduction of price competition might be a solution to the credence dilemma. Huck et al. (2012) show in an experiment that in a market for experience goods, competition has striking effects by increasing trust rates in a trust game by 36% points, the efficiency rate by 43% points and consequently overall welfare significantly. Dulleck et al. (2011) show that when experts compete for consumers through price setting, this drives down overall prices and increases the volume of trade. Mimra et al. (2016a) confirm in their experiment the price-reducing effect and show that price competition significantly drives down experts' profits by shifting surplus to consumers. However, with price competition, experts seem to show higher rates of undertreatment and overcharging. In Schneider, Bizer (2017), we derive the conclusion that potential efficiency increases due to price competition crucially depend on market circumstances and could also prove negative.

Another strategy to solve the credence dilemma lies in allowing consumers to search for second or even more opinions. Wolinsky (1993) shows that the transaction costs for visiting multiple experts are crucial but this can lead to an overall welfare increase. This is in line with the results of Mimra et al. (2016b), showing that with the possibility for second opinions the rate of overtreatment significantly decreases and absolute market efficiency increases depending on the search costs. Nevertheless, in Mimra et al.'s experiment, the willingness to search for second opinions was significantly lower than theory had predicted. They attribute this to consumers possibly thinking that honest expert types were prevailing in the market. Therefore, it seems, that the threat of second opinions might already make experts less fraudulent. However, in a model with experts deciding on their effort in diagnosis, Pesendorfer, Wolinsky (2003) show that the possibility for second opinions neither lead to Pareto optimal outcomes - as this is not incentive compatible - nor to second-best outcomes, since experts' effort levels remain too low without fixing prices.

3 Experimental Design

Our experimental design builds on our theoretical model from Schneider, Bizer (2017), briefly outlined in the next section and applies some structures from Dulleck et al. (2011), Mimra et al. (2016a) and Mimra et al. (2016b). In each session, we have up to five markets, each comprising eight subjects. Within each market, subjects are randomly allocated to the role of consumer or expert, with $N = 4$ consumers and $M = 4$ experts. The allocation remains constant throughout all fifteen periods and no interaction takes place between the markets. Earned payoffs are denominated in ECU, accumulated over all periods and paid at the end of the experiment, where ECU 1 converts to EUR 0.05. The complete course of the game inclusive of the payoff structure is common knowledge to all subjects, as we use role-independent instructions that subjects have to read completely before the actual role allocation.[1] Notice that we use neutral language throughout the instructions as well as during the experiment to avoid framing. However, in our following description, we will apply the common terminologies.

In each period, every consumer has a new problem that is randomly determined by a numeric value between 0 and 1 with two decimal places, e.g. 0.12. Consumers are never directly informed about the actual value of their problem. To solve their problems, consumers have to visit experts to receive signals and buy a service based on a signal that they have received before in a given period. Like consumer problems, signals are presented as numeric values between 0 and 1 with two decimal places. A signal can be either correct or wrong for a given consumer. For a correct signal, the numeric value corresponds to the numeric value of this consumer's problem. In case the signal is wrong, the numeric value will differ from the problem's value. Whether a signal is correct or wrong is determined by the effort choice of a sending expert as well as his individual qualification. To model endogenous verifiability for consumers, they can visit multiple experts for a signal. While each expert can only be visited once, consumers can receive up to four signals per period. Like in Schneider, Bizer (2017), we exclude the improbable case that two matching signals can both be wrong. Therefore, in the program we implemented the notion that two matching signals reveal correctness with certainty. Subjects are informed about this instance in the instructions. In sum, consumers have to decide in each period whether and how many experts they want to visit for a signal and whether they want to buy a service based on a signal. Consumers can choose freely between all available experts in their market. Notice that a service can only be bought from an expert who formerly has sent a signal. If a consumer buys a service based on a correct signal, she gains a payoff $V = 13$ ECU and ECU 0 if the signal is wrong. To receive a signal or service, consumers have to pay a price that is either fixed or chosen individually by the experts in each period. In *Fix* treatments, consumers have to pay $d = 2.20$

[1] The translated instructions can be found in the appendix. Original instructions in German are available on request.

ECU for a signal, including a fee modeling real life transaction costs of $s = 0.20$ ECU[2], and $p = 5$ ECU for a service. In *Flex* treatments, experts decide freely on their prices for a signal and a service in each period. At any time, consumers have the option to leave the market but have to bear the incurred costs up to that point. In order to allow for appropriate earnings by subjects, we give each consumer an endowment of ECU 12 per period. All incurred costs and earned profits during a period are added to or subtracted from this endowment. While making their decisions, consumers are informed about the prices and their costs incurred so far in the actual period. The consumers' decision screen is displayed in Figure 1.

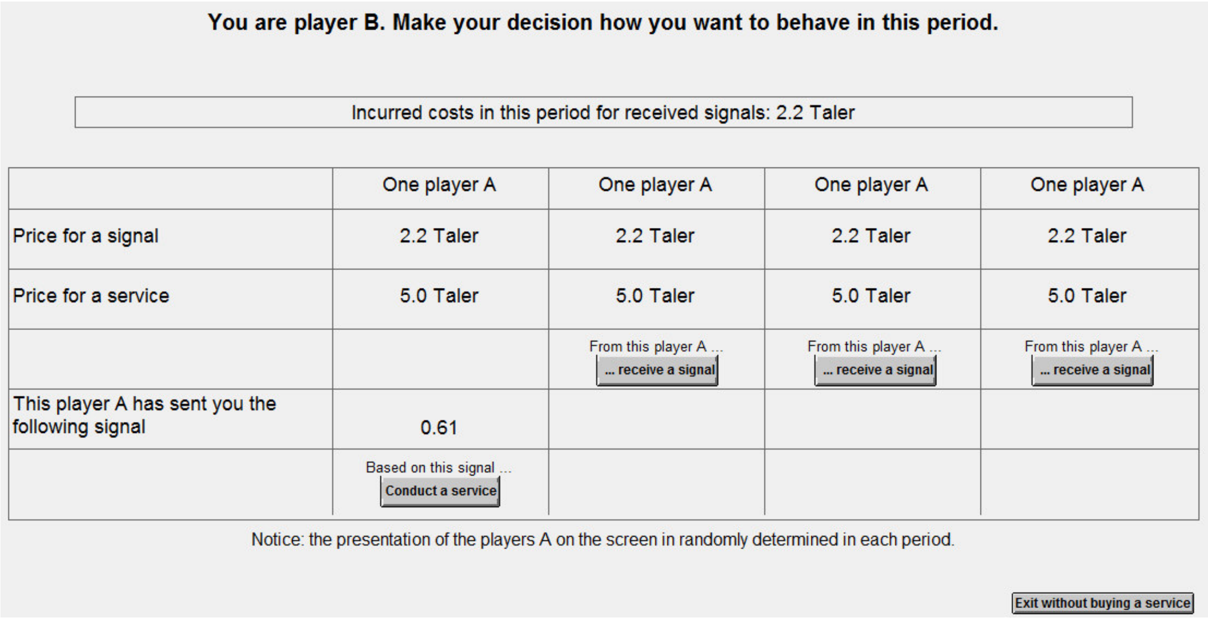
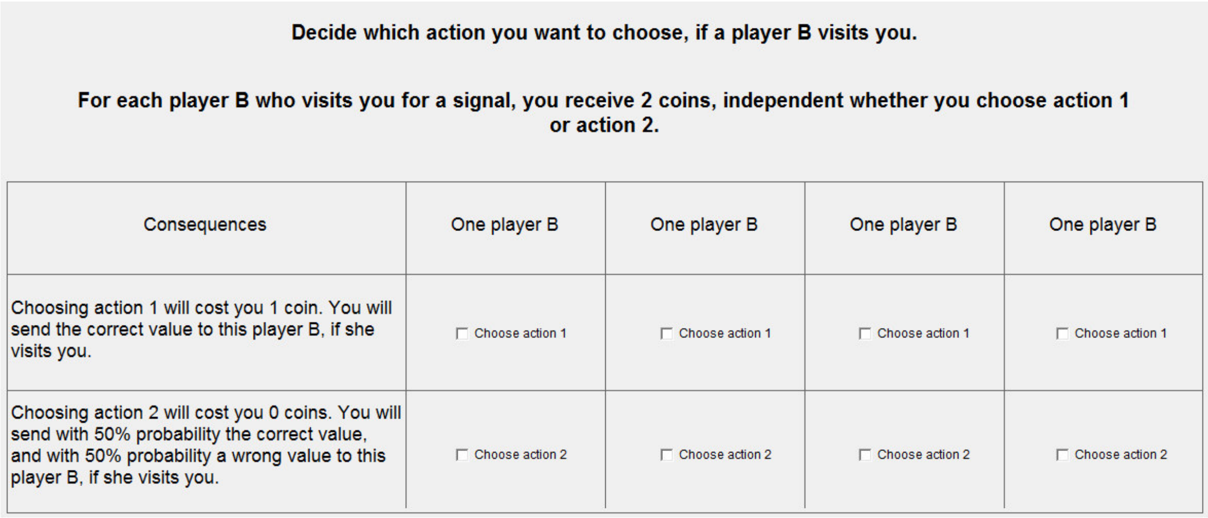


Figure 1: Consumers' decision screen.

Subjects allocated to the role of experts have to decide how much effort they want to invest in their diagnosis for the case that they are visited by consumers. Experts have the choice to invest either high or low effort. With their effort choices being unobservable to consumers and high effort being costly with $c = 1$ ECU, experts have a moral hazard problem. For simplification, we assume that low effort is free. We use the strategy method for effort decisions, implying that each expert decides in advance about how he wants to treat each single consumer in his market in case that she visits him for a signal. Therefore, in each period, all experts make four effort choices concerning whether they want to invest high or low effort in their diagnoses. If an expert decides to invest high effort, he will send a correct signal to this consumer with certainty. If an expert opts for low effort, the consequences depend on his individual skill level: at the beginning of the experiment, each subject who is allocated to the role of an expert receives the attribute of being either high or low skilled. The allocation is random and the proportions of high- and low-skilled experts depend on the underlying treatment. In *low* treatments, the share of high-skilled experts is given by $a = 0.25$. In *high* treatments, the share of high-skilled experts

[2]Notice that in *Flex* treatments consumers also have to pay the transaction costs $s = 0.20$ ECU per received signal on top of the price demanded by an expert.

amounts to $a = 0.75$. If an expert is low skilled and chooses low effort, he will send a wrong signal with certainty. By contrast, if an expert is high skilled and chooses low effort, he will send a correct signal to this consumer with probability $y = 0.50$. The experts' effort decision screen is shown in Figure 2.


Decide which action you want to choose, if a player B visits you.

For each player B who visits you for a signal, you receive 2 coins, independent whether you choose action 1 or action 2.

Consequences	One player B	One player B	One player B	One player B
Choosing action 1 will cost you 1 coin. You will send the correct value to this player B, if she visits you.	Choose action 1	Choose action 1	Choose action 1	Choose action 1
Choosing action 2 will cost you 0 coins. You will send with 50% probability the correct value, and with 50% probability a wrong value to this player B, if she visits you.	Choose action 2	Choose action 2	Choose action 2	Choose action 2

Figure 2: Experts' effort decision screen.

While in *Fix* treatments prices for signals and services are given with $d = 2$ and $p = 5$, in *Flex* treatments, experts can decide freely what they want to charge in each period. By allowing experts to choose prices on their own and consumers to freely choose between all experts in a market, we allow for price competition like in Dulleck et al. (2011). For setting prices, all positive values between 0 and 15 ECU with one decimal place are allowed.[3] In *Flex* treatments, prior to their effort decisions each expert chooses his prices for the given period. The experts' price decision screen is displayed in Figure 3. In order to allow experts to adapt their prices to the market, all prices of the actual period are displayed to all experts while consumers make their decisions.

[3]Notice that while the amount of 15 ECU is arbitrarily chosen as an upper boundary, it is strictly irrational for consumers to accept any price above 13 ECU.

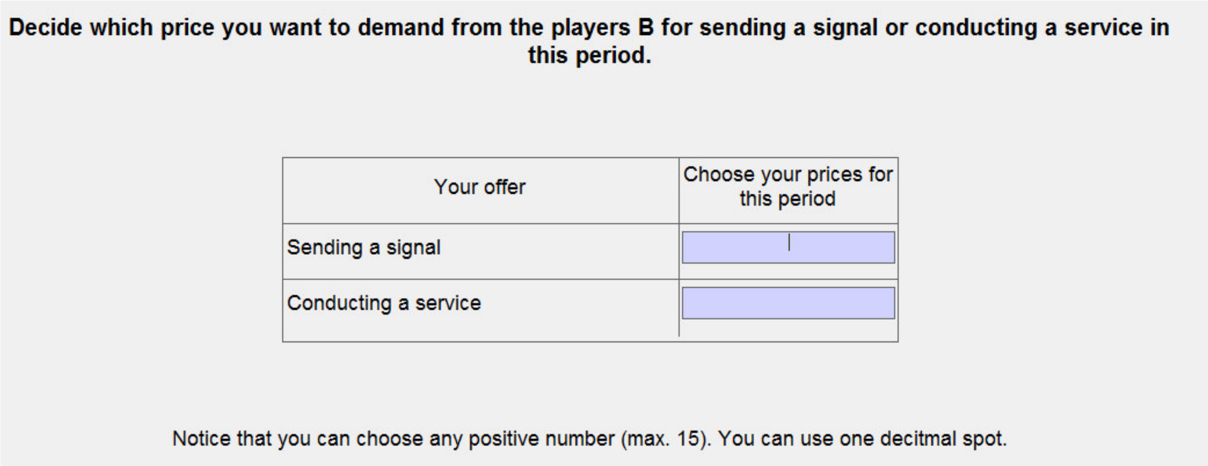


Figure 3: Experts' price decision screen.

To avoid consumers and experts identifying each other in the repeated interactions, i.e. avoiding individual reputations, we apply the random matching protocol by Dulleck et al. (2011). The presentation of consumers and experts on all screens is randomly determined in each period, which we outlined in the instructions and on the screens.

The experiment comprises fifteen periods with an identical course:

1. Nature determines the actual problem for each consumer through numeric value between 0.00 and 1.00, to two decimal places.
2. In *Flex* treatments, each expert sets his prices for a signal and a service.
3. Each expert decides upfront whether he will invest high or low effort in his diagnoses for each of the $N = 4$ consumers in his market.
4. Consumers decide how many experts they want to visit for a signal and whether they want to buy a service based on any received signal. Meanwhile, experts are informed about the other experts' prices in their market.
5. Decisions are implemented and each subject receives a summary of the results. [4]

3.1 Treatment conditions

We implement four experimental treatment conditions, using a standard 2x2 design, in which we vary the share of high-skilled experts and whether price competition exists.

FixLow Prices for signals and service are fixed. In each market there is a share of $a = 0.25$ of high-skilled experts.

[4] Consumers receive a summary of how many experts they have visited, whether they have bought a service and their payoff from a potentially-bought service inclusive of their endowment of 12 ECU. Experts are informed about which prices they chose, how many consumers visited them, how many times they decided for high and low effort for their visitors and how many of them bought their service. Additionally, all subjects are informed of how much they have earned in the current period, as well as over all periods thus far.

FlexLow: Experts set their own prices for signals and service in each period. In each market there is a share of $a = 0.25$ of high-skilled experts.

FixHigh Prices for signals and service are fixed. In each market there is a share of $a = 0.75$ of high-skilled experts.

FlexHigh: Experts set their own prices for signals and service in each period. In each market there is a share of $a = 0.75$ of high-skilled experts.

3.2 Procedure

For *FixLow* / *FlexLow* / *FixHigh* / *FlexHigh*, altogether 88/88/88/96 subjects took part in the experiment, in sum 360. Consequently, we receive 11/11/11/12 independent markets per treatment which we will use as independent observation in the results section. Experiments were conducted with a standard subject pool across disciplines in the KD^2 Lab at the Karlsruher Institute for Technology (KIT) within two weeks in July/August 2017. Subjects were recruited by using HROOT (Bock et al., 2014) and the experiment was programmed using z-Tree (Fischbacher, 2007). All subjects participated only in one session which lasted approximately 60 minutes, whereby subjects earned 11.33 EUR on average. This included a show-up fee for subjects allocated to the role of experts (the counterpart of consumers' endowment) of 7.00 EUR. According to the relative complexity of our design and the written instructions, we let all subjects answer a set of control questions to ensure understanding. At the end of the experiment, we used a standard questionnaire to control for subjects' demographics.

4 Theoretical Analysis and Hypothesis

In the following, we derive our hypotheses for consumer and expert behavior and effects on market efficiency. We start with a brief summary of the underlying theoretical model from Schneider, Bizer (2017), as we will derive our hypothesis from it. We subdivide our hypothesis in three parts: (i) the expected outcome regarding experts' moral hazard problem in a market with credence goods and heterogeneously-qualified experts; (ii) the effects of expert qualification, i.e. an increased share of high-skilled experts in a market; and (iii) the introduction of price competition.

4.1 Theoretical Model

Assume a market with N experts and M symmetric consumers. The game has $n \geq 1$ periods. In each period, all consumers have a new problem given by $i \in [0, 1]$. To solve their problem and receive a positive payoff $V > 0$, consumers have to buy a service $b \in [0, 1]$ based on a correct and formerly-received signal. Each consumer can visit up to $n = N$ experts to receive such a signal. We exclude individual reputation building by assuming that consumers cannot identify individual experts. Additionally, experts cannot observe consumers' histories, i.e. whether one has visited another expert before. Experts offer a contract (d, p) to consumers with d as the price for a signal and p as the price for a service. When a consumer decides to visit an expert for a signal, she has to bear the costs d and transaction costs s. The visited expert decides how much effort he wants to invest in sending his signal. He can invest either high effort for costs $c > 0$ or low effort for free. If an expert invests high effort, he will send a correct signal to the consumer with certainty. By contrast, if he invests only low effort, the consequences will depend on this expert's attribute $t \in \{h, l\}$. Each expert receives with probability $a \in (0, 1]$ the attribute high-skilled, i.e. $t = h$, and with probability $1 - a$ the attribute low-skilled, i.e. $t = l$. If a low-skilled expert invests low effort in sending a signal, he will send a wrong signal with certainty. If a high-skilled expert invests low effort, he has a chance $y \in (0, 1]$ that he will nevertheless send a correct signal. Let x_l [x_h] be the probability that an expert with low [high] skill chooses high effort. As consumers are unable to observe neither experts' effort choices nor their individual skills, they react to the expected probability $z = ax_h + (1 - a)x_l + a(1 - x_h)y$ that a randomly visited expert sends a correct signal. In the following, we describe the possible equilibria that will be repeatedly played over all fifteen periods of the game.

Lemma 1: A consumers' best response to (d, p, z) is given by: (i) receive one signal and buy the corresponding service; (ii) receive signals until two of them match, then buy the service from one of the two experts with matching signals; and (iii) leave the market without any action.

Proof of Lemma 1: See Schneider, Bizer (2017).

□

Let a consumer's probability of buying after her first signal be given by $f \in [0, 1]$, if she enters the market. A consumer's probability of searching for matching signals is given by $1 - f$. Consumers' expected duration of search, i.e. how many experts they will visit, is thus given by

$$S = f + (1 - f)\frac{2}{x_h a + (1 - a)x_l + (1 - x_h)ay}.$$

Experts will choose x_t in reaction to f and their individual attribute. Let f_t^* be the critical value for consumers to buy after their first signal that makes experts of type t indifferent between high and low effort:

$$f_t^* = \frac{1 - \frac{2c}{p(1-q_t y)}}{1 + \frac{c(z-2)}{p(1-q_t y)}},$$

with $q_h = 1$ and $q_l = 0$. To make high-skilled experts indifferent, consumers need to search for matching signals more often. Experts' reaction function is given by

$$x_t(f) = \begin{cases} x_t = 0 & \text{if } f > f_t^* \\ x_t \in \{\underline{x_t^*}, \overline{x_t^*}\} & \text{if } f = f_t^* \neq 0 \\ x_t \in [\underline{x_t^*}, \overline{x_t^*}] & \text{if } f = f_t^* = 0 \\ x_t = 1 & \text{if } f < f_t^*, \end{cases}$$

with

$$\underline{x_l^*}, \overline{x_l^*} = \frac{\frac{V+d+s}{2V} - ay \pm \sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d)}{V}}}{1-a},$$

and

$$\underline{x_h^*}, \overline{x_h^*} = 1 + \frac{1 - (\frac{V+d+s}{2V} \pm \sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d)}{V}})}{a(y-1)}.$$

Lemma 2: Every equilibrium in pure strategies is a degenerate equilibrium, i.e. with experts choosing $x_l, x_h = 0$ and consumers leaving the market without any action.

Proof of Lemma 2: Assume that consumers never search for matching signals, i.e. $f = 1$. Experts have an incentive to never invest high effort in their diagnosis, since every consumer who is on a visit will buy his service instantly. Anticipating this, experts will never invest in high effort and consumers will leave the market. By contrast, assume that consumers are always searching for matching signals, i.e. $f = 0$. Experts only have a chance to sell a service at price p if they send a correct signal, as consumers always opt for a verification. With p being sufficiently high and c being relatively low in comparison, experts will always choose $x_{,l}, x_h = 1$. With experts always investing in high effort, there is no longer a need for consumers to search for matching opinions and they will switch to $f = 1$. Now, experts no longer have any incentive to invest in high effort and will always choose low effort. This leads consumers again to leave the market. Following Pesendorfer, Wolinsky (2003), we will call this kind of equilibrium a degenerate equilibrium, as experts never invest in high effort and consumers always leave the market without any action.[5]

□

Lemma 3: If $x_h = 0$, low-skilled experts will balance z that $z \in [\underline{z}, \overline{z}]$[6], as long as $a(1-y) \leq 1-z$ and $y \leq \frac{z}{a}$. If $x_l = 1$, high-skilled experts will balance z that $z \in [\underline{z}, \overline{z}]$, as long as $a(1-y) \geq 1-z$.

Proof of Lemma 3: See Schneider, Bizer (2017).

□

Through the introduction of heterogeneous experts, consumers are no longer able to choose a uniform value f that makes all experts indifferent. Assuming that market participation

[5]Notice that there is a theoretical possibility with high-skilled experts in the market that consumers have an incentive to enter even with experts restraining from high effort. If the share of high-skilled experts in the market in combination with their degree of qualification is relatively high and z exceeds a necessary threshold, consumers will enter the market regardless. For more details, see Schneider, Bizer (2017). However, we will exclude this case here as it is not relevant given our experimental set-up.

[6]Notice that $\underline{z}$ and $\overline{z}$ are the roots of the quadratic equation for making consumers indifferent between buying after one signal and searching for matching signals. To enable a mixed strategy equilibrium, z needs to lie within this interval.

is worthwhile, consumers will apply a strategy to make either high- or low-skilled experts indifferent. According to their reaction function, the other expert type will choose a pure strategy, i.e. $x_h = 0$ or $x_l = 1$. To enable a mixed strategy equilibrium, experts need to make consumers indifferent between buying after one signal and searching for matching signals, which implies that the probability of receiving a correct signal needs to remain within the given interval $z \in [\underline{z}, \overline{z}]$. With one expert type choosing a pure strategy, the other type needs to balance z, with its possibility depending on the market composition. According to Lemma 3, we can define the following adaptation conditions

$$a(1-y) \leq 1-z, \tag{1}$$

$$ay \leq z, \tag{2}$$

$$a(1-y) \geq 1-z. \tag{3}$$

For low-skilled experts being able to balance z, (1) and (2) needs to be fulfilled. We will refer to this as a low-skill equilibrium. For high-skilled experts to balance z, (3) needs to hold. We will refer to this as a high-skill equilibrium. We will exclude the case that $a(1-y) = 1-z$. Therefore, only (1) or (3) can hold and there is only the possibility of either high-skill or low-skill equilibria. According to the defined interval for z, both types of equilibria have a corresponding interval for f_t^* that makes the balancing expert type indifferent.

Whether a mixed strategy equilibrium is possible depends on the market composition, i.e. the share of high-skilled experts a, their degree of qualification y and the overall number of experts N, as well as the market circumstances, i.e. the service price p, the diagnosis costs d, the transaction costs s and consumers' payoff for a solved problem V. Assuming fixed prices in the first step, we derive the following equilibrium behavior:

Lemma 4: *Depending on the fixed price ratio $2c/p$ there exist several types of non-degenerate equilibria with the fixed profile (d, p, z, f), assuming all necessary conditions*[7] *are fulfilled: (i) With $2c \leq p$, consumers will choose $f = f_l^*$, if the first (1) and second (2) adaptation condition hold. Low-skilled experts will choose either $x_l \in \{\underline{x_l^*}, \overline{x_l^*}\}$ if $p = 2c$, or $x_l \in [\underline{x_l^*}, \overline{x_l^*}]$ if $p > 2c$, while high-skilled experts always choose $x_h = 0$; (ii) with $2c/(1-y) \leq p$, if the third adaptation conditions(3) holds, consumers will choose $f = f_h^*$. There high skilled experts will choose either $x_h \in \{\underline{x_h^*}, \overline{x_h^*}\}$ if $p = 2c/(1-y)$, or $x_h \in [\underline{x_h^*}, \overline{x_h^*}]$ if $p > 2c/(1-y)$, while low-skilled experts will always choose $x_l = 1$.*

Proof of Lemma 4: See Schneider, Bizer (2017).

□

[7] For more details on these conditions see Schneider, Bizer (2017).

Letting experts choose their prices freely, we will derive different kinds of non-degenerate equilibria.

Lemma 5: *For the profile (d, p, z, f) being a non-degenerate flexible price equilibrium, similar market conditions as for fixed price equilibria must hold. All experts offer identical contracts with $d = 0$. Moreover, $s \in [0, \tilde{s}]$ with $\tilde{s} = V(2\sqrt{5} - 2)/8 + 4\sqrt{5}$, $z = \underline{z} = \frac{V+s-\sqrt{(V+s)^2-8sV}}{2V}$, and $f = f_t^* = 1 - \frac{2c}{p(1-q_t y)}/1 + \frac{c(z-2)}{p(1-q_t y)}$. According to the market composition, there are two possible outcomes: (i) with $ay \leq z$ and $a(1-y) < 1-z$, there will be $x_h = 0$, $x_l = \underline{x_l^*} = (\underline{z} - ay)/(1-a)$ and $f = f_l^*$, with the possible price range given by $p \in [2c, V - \frac{2c}{z}]$; and (ii) with $a(1-y) \geq 1-z$ there will be $x_l = 1$, $x_h = \underline{x_h^*} = (\underline{z} - 1 + a(1-y))/(1-a)$ and $f = f_h^*$, with the possible price range given by $p \in [\frac{2c}{1-y}, V - \frac{2c}{z}]$*

Proof of Lemma 5: See Schneider, Bizer (2017).

□

Notice that with flexible prices, $z \in \{\underline{z}, \overline{z}\}$. As there is no possibility for $\overline{z}$ to lie within the required interval $z \in [\frac{s(3-\sqrt{5})}{2V}, \frac{s(3+\sqrt{5})}{2V}]$, only $\underline{z}$ can be a flexible price equilibrium.[8] In terms of welfare, degenerate equilibria are inferior, as no trade takes place with experts not making any profits and consumer problems remaining unsolved. In this case, consumers and experts will earn a profit of zero or rather their outside option. In a non-degenerate equilibrium, a consumer's expected payoff is given by

$$\pi_c(f, z) = f(zV - p - (s + d)) + (1 - f)(V - p - \frac{2(s + d)}{z}),$$

with $f = f_t^* = 1 - \frac{2c}{p(1-q_t y)}/1 + \frac{c(z-2)}{p(1-q_t y)}$ and $z = ax_h + (1-a)x_l + (1-x_h)ay \in [\underline{z}, \overline{z}]$. An individual expert's expected payoff, depending on his attribute t, is given by

$$\pi_e^t(x_t, q_t, f) = \frac{M}{N}[S_t(d - x_t c) + fBp + (1 - fB)\frac{p}{2}(x_t(1 - q_t y) + y)],$$

with $fB = f_t^* B = 1/(1 + \frac{2c}{p(1-q_t y)-2c})$, $S_t = f_t^* + 2(1 - f_t^*)/z$, N as the total number of experts and M as the total number of consumers in the market. Combining the welfare functions, overall welfare is given by

$$\pi(f_t^*, z, a, y, k) = k[f_t^*(zV - s - c(z - (1 - x_h)ay) + (1 - f_t^*)(V - \frac{2s}{z} - 2c + \frac{2c}{z}(1 - x_h)ay)].$$

4.2 Predictions and Hypothesis

We define parameters from our theoretical model as described in our experimental design. Table 1 presents fixed parameters across all treatments. Let $\overline{a}$ $[\underline{a}]$ be the value of a that defines the critical value at which $a(1-y) = 1-z$, given $\overline{z}$ $[\underline{z}]$.[9]

[8] This derives from the boundary of s in all non-degenerate equilibria with $s \leq \overline{s} = V(3 - 2\sqrt{2})$.

[9] We do not display the second adaptation condition, as we chose parameter values whereby it is always fulfilled.

Table 1: Fixed parameters across treatments

Parameters	V	s	c	y	$\overline{a}$	$\underline{a}$
	13	0.2	1	0.50	0.72	0.95

Table 2 provides an overview of our treatment variables and the expected expert/consumer behavior, as well as the expected market efficiency. In *FixLow* we predict consumers to play their strategy for a low-skill equilibrium, while in *FixHigh* they will switch to the high-skill equilibrium. With consumers' expected payoff becoming negative with $\underline{z}$ and fixed prices, $\overline{z}$ is the only feasible equilibrium. In both treatments with price competition, we predict a market breakdown. Since only $\underline{z}$ can be a flexible price equilibrium, in combination with stricter requirements for maximum transaction and signal costs, i.e. $s+d < V(2\sqrt{5}-2)/8+4\sqrt{5} \approx 1.89$, a non-degenerate equilibrium becomes impossible. Consequently, we expect consumers to always leave without any action and all experts to choose strictly low effort.

Table 2: Theoretical predictions

Treatment variables	*FixLow*	*FlexLow*	*FixHigh*	*FlexHigh*
a: Share high skilled experts	0.25	0.25	0.75	0.75
d: Average signal price	2.00	0.00	2.00	0.00
p: Average service price	5.00	[2.00,6.65]	5.00	[4.00,8.15]
Expert behavior				
$\underline{z}/\overline{z}$: Prob. correct signal	- / 0.64	0.00 (0.03) / -	- / 0.64	0.00 (0.03) / -
x_h: High effort high skilled	0.00	0.00	0.05	$x_h^*/0.00$
x_l: High effort low skilled	0.69	x_l^*	1.00	$1.00/x_l^*$
Consumer behavior				
f: Buy after first signal	0.82	0.00	0.44	0.00
$1-f$: Matching signals	0.18	0.00	0.54	0.00
Leaving instantly	0.00%	100.00%	0.00%	100.00%
S: Visited experts	1.37	0.00	2.19	0.00
Market efficiency				
π_c: Consumer welfare	197.25	180.00	197.25	180.00
π_e^h: High skilled' profits	93.75	0.00	94.80	0.00
π_e^l: Low skilled' profits	82.35	0.00	77.85	0.00
π: Overall welfare	285.30	180.00	283.58	180.00
Solved problems	70.48%	0.00%	82.16%	0.00%
Efficiency rate	76.61%	48.39%	76.23%	48.39%
Trade volume	100.00%	0.00%	100.00%	0.00%
Wrong Services	29.52%	0.00%	15.84%	0.00%

Baseline Market and General Predictions

As we choose parameter values whereby consumers and experts can expect a positive payoff from trade, we predict all subjects to play their mixed strategy equilibrium. Consumers will

choose the mixed strategy that makes the type of experts indifferent between high and low effort, who are able to balance z. As we assume *FixLow* as our baseline treatment, this implies that $f = f_l^*$, as outlined by the adaptation conditions. Experts will choose their effort according to their reaction function and balance $z = \overline{z}$: high-skilled experts will always choose low effort with $x_h = 0$ and low-skilled experts will play their mixed strategy with $x_l = x_l^*$.
In addition to our prediction for the baseline market, we expect some behavioral patterns across all treatments. High-skilled experts are always expected to invest less effort than low-skilled experts. This derives from high-skilled experts needing a higher rate of consumers searching for matching opinions to become indifferent. Referring to other experiments, we do not expect subjects to start by playing their mixed strategies unanimously. It seems more plausible that subjects tend to adapt their behavior by individual experiences with learning effects over periods. We expect that consumers will show strong reactions to the prevalent probability for receiving a correct signal, i.e. z, and experts will adapt their effort investments according to consumers' search behavior, i.e. f.

Hypothesis 1 ("General Predictions")

H1a) In our baseline market, experts will balance z that $z = \overline{z}$.

H1b) In our baseline market, consumer will choose $f = f_l^*$.

H1c) In our baseline market, experts will choose $x_t \in \{x_h = 0, x_l^*\}$.

H1d) In our baseline market, consumers will never leave the market without buying a service.

H1e) High skilled experts will invest less effort than low-skilled experts.

H1f) Subjects will show learning effects according to their opponents' average behavior within their market.

Effects of Expert Qualification
By increasing the share of high-skilled experts in the market, low-skilled experts are no longer able to balance z in *FixHigh*. In anticipation, consumers are expected to change their search behavior by increasing the probability of searching for matching opinions. This should make high-skilled experts indifferent regarding who will choose $x_h = x_h^*$ to balance z. With consumers searching for matching opinions more often, the duration of search S increases, implying a welfare loss by higher transaction costs. At the same time, the share of solved problems will increase while the share of wrong treatments will decreases resulting in an increase of overall welfare. In sum, these effects will almost counterbalance each other which leaves the expected efficiency rate unchanged. However, with low-skilled experts being forced to invest more high effort to attract a comparable share of consumers, their profits will decrease. With flexible prices, there is theoretically no possibility for a non-degenerate equilibrium. Assuming that consumers will nevertheless participate, we expect the range of possible service prices to decrease if consumers choose the high-skilled equilibrium, because high-skilled experts need a

higher minimum service price to invest in high effort.

Hypothesis 2 ("Effects of Expert Qualification")

H2a) With fixed prices, the effort choice of all experts increases, i.e. $x_h = x_h^*$ and $x_l = 1$.

H2b) With fixed prices, consumers will choose the high skill equilibrium with $f = f_h^* < f_l^*$ and the duration of search S will increase.

H2c) With fixed prices, there is no effect on the market efficiency rate but more consumer problems are solved and fewer wrong services are conducted.

H2d) There is no ceteris paribus effect on z by increasing the share of high skilled experts in the market.

H2e) With price competition, there is no effect of expert qualification.

Effects of Price Competition
By letting experts choose their contracts (d, p) on their own, we allow for flexible prices in *Flex* treatments. Regarding the price for signals, the only possible equilibrium in theory is $d = 0$, independent of the share of high-skilled experts in the market. Experts are unable to signal their attribute, since consumers cannot identify neither individual experts nor their degree of qualification. With the costs d being sunk the moment when an expert decides on his effort, they do not affect this decision. Consequently, consumers will strictly prefer a lower d and experts will undercut any $d' > 0$ to attract more consumers. With $d = 0$, there is no possibility for a mixed strategy equilibrium with flexible prices, as only $\underline{z}$ could be stable. Consequently, consumers are expected to prefer leaving the market without any action and experts will always choose low effort. Assuming that consumers will not leave the market instantly, we would expect no differences in experts' price setting behavior according to their attribute, since they cannot credibly signal their type, even by price setting. With consumers participating, there is a broad range of possible prices for a service. This derives from f and p counterbalancing each other in equilibrium: the higher the price for a service, the more often consumers buy after their first recommendation. Therefore, we expect a strong correlation between the factors.

Hypothesis 3 ("Effects of Price Competition")

H3a) The price for signals will be zero, i.e. $d = 0$.

H3b) Experts' effort choices are independent of d.

H3c) The price for services will lie strictly above its defined minimum.

H3d) There will be no different price setting by high- and low-skilled experts.

H3e) There will be a market breakdown with consumers leaving instantly.

H3f) If markets do not break down, service price p is correlated with f.

5 Results

In this chapter, we will present our experimental results. In the first section, we outline our methodology for analyzing our data. The subsequent structure is according to our hypotheses. We start by investigating the general behavior in our baseline market, i.e. *FixLow*. Subsequently, we will look at the effects of expert qualification and by introducing price competition.

5.1 Methodology

With subjects interacting in the same market over all fifteen periods, market reputation will arise even though we excluded reputation building at the individual level by the random presentation protocol. Therefore, we use market averages (a market comprises of four experts and four consumers) as independent observations. In accordance, we will analyze prices in *Flex* treatments at the group level. To determine market efficiency, we will use four indicators: (i) the share of solved problems; (ii) the volume of trade, given by the share of consumers buying a service; (iii) the efficiency rate, given by the share of welfare actually realized in relation to the maximum possible welfare[10]; and (iv) the share of services based on a wrong signal.

In general, we apply non-parametric tests, i.e. the Wilcoxon signed-rank test (WSR) and the Wilcoxon-Mann-Whitney test (MWU), to identify differences regarding our predictions and between our treatments. To show the effect of expert qualification, we will compare *FixLow* with *FixHigh*, and *FlexLow* with *FlexHigh*. To show the influence of price competition, we will compare *FixLow* with *FlexLow*, and *FixHigh* with *FlexHigh*. This enables us to show the influence of these effects in distinct markets. In order to test for learning effects, we subdivide our data for experts' effort choices and consumers' search behavior in thirds, whereby each third comprises five periods.

We will complement our non-parametric tests with parametric tests. In accordance with Dulleck et al. (2011) and Mimra et al. (2016a), we will use random-effects panel tobit and probit regressions. This takes care of our challenging data structure with: (i) repetitions over fifteen periods of our game impose serial correlations between individual's decisions; (ii) with eight individuals interacting over fifteen periods within a single market, which potentially leads to correlated observations within the market. We use a probit regression for consumers' decision concerning whether to buy a service after they have received only one signal in a period and tobit regressions to determine the effects on experts' share of high-effort choices within a period, as well as the probability of a consumer receiving a correct signal from a random expert, experts' individual profits and consumers' individual welfare in a period.

[10] The maximum welfare per period in our market is given by ECU 24.80 and is realized when consumers receive one single correct signal and buy the corresponding service. The maximum welfare over all fifteen periods is thus given by ECU 372.

5.2 Baseline Market

Result 1 (Behavior and Efficiency with Experts' Moral Hazard Problem):

Experts: *High- and low-skilled experts invest significantly more effort in their signals than theory predict for equilibrium behavior, resulting in a significantly higher-than-expected probability of consumers receiving a correct signal. High-skilled experts invest significantly less effort in comparison to low-skilled experts. In sum, experts invest less effort than would be optimal for them, given consumer behavior.*

Consumers: *Consumers behave risk averse, buying significantly less often than predicted after one signal and searching predominately for matching signals. They buy on average significantly more signals and apply non-rational strategies, i.e. leaving without any action and buying after non-matching signals.*

Market Efficiency: *Our baseline market is significantly more efficient than predicted with higher overall welfare. This is driven by higher low-skilled experts' profits. While many consumers leave the market without buying a service, thus reducing the volume of trade, this does not undermine the expected share of solved problems, as the services bought are predominantly based on correct signals.*

In Table 3, we present an overview of the results in *FixLow* in comparison with our predictions. We use this treatment as the baseline condition and compare the results according to our predictions to derive subjects' general behavior in a market for credence goods with a relatively low share of high-skilled experts and a moral hazard problem for experts in their diagnosis.

Expert Behavior

According to Hypothesis 1a, we predicted experts to balance their high-effort investments at $z = 0.64$. Our results show that the actual probability of consumers receiving a correct diagnosis from a random expert lies at 73.75%, significantly above this value (WSR: $z = 2.670$, $p < 0.01$). By looking at the different types of experts, it shows that both invest significantly more than the predicted, with 44.45% for high-skilled experts (WSR: $z = 2.937$, $p < 0.01$) and 74.24% for low-skilled experts (WSR: 2.134, $p < 0.05$), which contradicts Hypothesis 1c. By comparing the different investment behavior of high- and low-skilled experts, we can confirm Hypothesis 1e in the baseline market, since experts significantly differ in their investments according to their type, with higher investments of low-skilled experts (WSR: $z = -2.667$, $p < 0.01$). In Figure 4 we provide an overview of expert and consumer behavior in our baseline market. By testing for learning effects, we observe a significant increase of high effort choices from the first to the second third for high-skilled experts (WSR: $z = -1.739$, $p < 0.10$) and a significant decrease from the second to the last third (WSR: $z = 2.101$, $p < 0.05$). Low-skilled experts show no signs of adapting their high effort choices over periods (WSRs: $p > 0.44$). Even though high-skilled experts' increase in investments from the first to the second third is according to our predictions, as consumers mainly search for matching opinions and investing more effort increases experts' expected profits, the subsequent decline and low-skilled experts'

Table 3: Overview of Results in Baseline (*FixLow*)

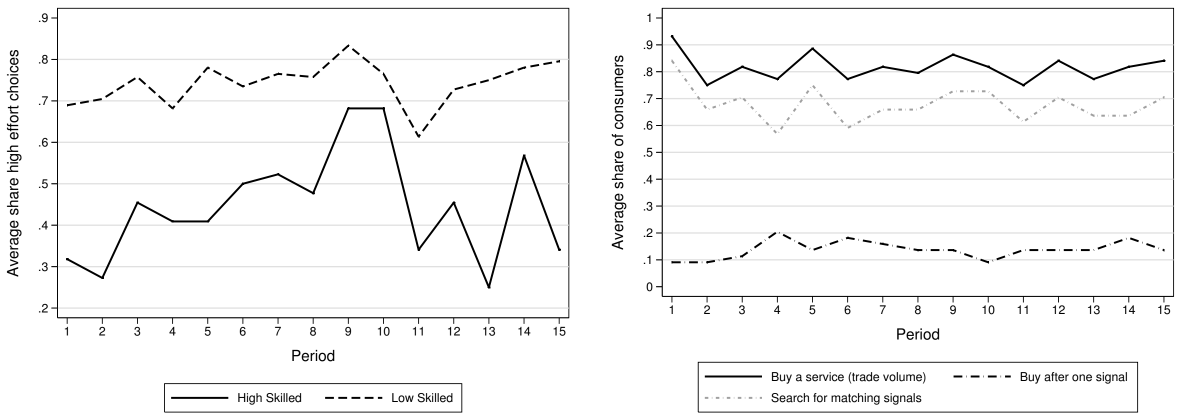
	FixLow	*Predictions*
Expert behavior		
z: Prob. correct signal	73.75% (.068)*	64.00%
x_h: High effort high skilled	44.55% (.263)*	0.00%
x_l: High effort low skilled	74.24% (.061)*	68.95%
Consumer behavior		
f: Buy after first signal	13.79% (.134)*	82.00%
$1-f$: Matching signals	67.88% (.175)*	18.00%
Rational strategies	81.67% (.154)*	100.00%
Leaving instantly	10.60% (.122)*	0.00%
S: Visited experts	2.04 (.46)*	1.37
Market efficiency		
π_c: Consumer welfare	199.57 (24.15)	197.25
π_e^h: High skilled' profits	99.27 (30.60)	93.75
π_e^l: Low skilled' profits	103.00 (17.84)*	82.35
π: Overall welfare	301.64 (24.13)	285.30
Solved problems	76.06% (.145)*	70.48%
Efficiency rate	81.01% (.065)*	76.61%
Trade volume	81.67% (.154)*	100.00%
Wrong Services	6.74% (.046)*	47.52%
Number of Subjects	88	

All given values are market averages across periods with clustered standard deviations in parentheses.
* Significant differences to our predictions ($p < 0.10$).

absence of learning effects lead to a rejection of Hypothesis $1f$ for experts in our baseline market.

Consumer Behavior

According to experts' higher-than-expected investment rates and the resulting higher rate of z, it would be rational for consumers to increase their purchases after receiving only one signal above the predicted rate of $f = 0.82$. By contrast, with 13.79% f even lies significantly below our predictions (WSR: $z = -2.941$, $p < 0.01$). Additionally, with 67.88% consumers search significantly more often than predicted for matching signals (WSR: $z = 2.936$, $p < 0.01$). Figure 4 displays that these patterns are consistent between all thirds of the experiment (WSR: $p > 0.58$), contradicting Hypothesis $1f$, as we expected an adaptation to experts' high effort investments. With with 81.67% the volume of trade lies below the predicted rate of 100% (WSR: $z = -2.937$, $p < 0.01$). In sum, this contradicts Hypothesis $1b$ and leads to a significantly higher number of consulted experts with $S = 2.04$ on average (WSR: $z = 2.847$, $p < 0.01$). A considerable share of consumers restrain from defined rational strategies with only 81.67% choosing to purchase either after one signal or after matching signals. For example, according to the prevalent prices and the higher probability of a correct signal, consumers should never abstain from trade. Nevertheless, 10.60% of consumers leave the market without any action and 7.27% buy a service based on non-matching signals, thus contradicting Hypothesis 1d.



(a) Experts effort choice

(b) Consumer behavior

Figure 4: Expert and Consumer Behavior in Baseline (*FixLow*)

Market Efficiency

With 76.06% of consumer problems solved, this share is according to our expectations of 70.48% (WSR: $z = 1.245$, $p > 0.21$). This is surprising upon first glance because 10.60% of consumers leave the market without any action and 7.73% leave without buying a service. Consequently, 18.33% of problems remain unsolved according to not even having been attempted to be solved. However, with only 6.73% of bought services being based on a wrong signal, this share is significantly lower than the expected share of 29.52% (WSR: $z = -2.936$, $p < 0.01$). The efficiency rate of 81.01% is weakly significantly higher than the predicted rate of 76.61% (WSR: $z = 1.867$, $p < 0.10$). This effect is mainly driven by low-skilled experts' average profits being $\pi_e^l = 103.00$, namely significantly above our predictions (WSR: $z = 2.580$, $p < 0.01$). By contrast, consumers' high share of irrational strategies and their risk averse behavior does not significantly reduce their welfare but lies at $\pi_c = 199.57$, which is close to our expectations (WSR: $p > 0.47$). This also accounts for high-skilled experts' profits with $\pi_e^h = 99.27$ (WSR: $p > 0.53$).

Remarks: In sum, consumers behave risk averse in our market, although efficiency is significantly higher than theory predicts. Consumers prefer to search for matching opinions much more often than expected and restrain from buying after their first signal almost completely. This leads to higher search rates and welfare losses according to higher transaction costs on the one hand. Regarding expert behavior, our theory predicts that if consumers choose $f < f_t^*$ they will increase their effort choices to $x_t = 1$. With $f = 0.14$ this is given for both expert types. While we actually observe higher effort choices than predicted for equilibrium, both types fall short of their best response. Across periods, high-skilled experts increase their effort levels on average from about 30% to almost 70% in period 9 and 10. It is surprising that their effort levels subsequently decrease again, while low-skilled experts' levels are quite stable across periods. However, since low-skilled experts choose high effort more often on average, which even outbalances their disadvantage of having lower skill in diagnosis, they profit disproportionately from consumers' risk aversion as they provide a higher probability of a correct signal and thus sell more services. Nevertheless, it is surprising that while a considerable share of subjects restrain from optimal behavior, the efficiency rate lies above our predictions. This results from fewer wrong services being conducted, i.e. based on a wrong signal, in which case consumers gain no positive payoff (except their remaining endowment). As a bought service is only a shift in terms of welfare from consumers to experts, the pure number of conducted treatments cannot account for an increase or decrease in overall welfare, but rather its quality. Consequently, while higher search rates for matching signals induce welfare losses in the form of higher transaction costs, these are overcompensated by higher efficiency rates from services with higher quality.

5.3 Effects of Qualification

Result 2 (Behavior and Efficiency according to Expert Qualification):

Experts: *We observe a significant increase in effort for low-skilled experts with fixed prices, which also increases consumers' probability of receiving a correct signal. With price competition, high-skilled experts invest significantly more effort due to expert qualification. With fixed prices, experts' investments remain under their optimal response. With price competition, high-skilled experts invest too much and low-skilled experts too little, given actual prices and consumer behavior. Average prices remain unaffected by expert qualification.*

Consumers: *Consumers behave on average less risk averse than before, as they increase their purchases after their first signal as well as the use of rational strategies, and leave the market less often without any action. Only with fixed prices is the higher frequency of rational strategies significant. Given experts' actual behavior, consumers still act risk averse than would be optimal.*

Market Efficiency: *With fixed prices, market efficiency significantly increases with more solved problems, a higher volume of trade and a higher efficiency rate, with increased welfare for consumers and profits for all expert types. With price competition, these effects vanish with no significant changes to expert qualification, but high-skilled experts' profits are weakly reduced.*

Table 4 provides an overview of our experimental results across all treatments. We state different results concerning whether price competition is prevalent (*FlexLow* vs. *FlexHigh*) or not (*FixLow* vs. *FixHigh*).

Expert Behavior

According to Hypothesis 2a, we expected that all experts' effort choices should increase by qualification. Indeed, average effort rates of all types increase. However, these increases are only weakly significant for high-skilled experts in a market with price competition (MWU: $z = -1.786$, $p < 0.10$) and for low-skilled experts in a market without price competition (MWU: $z = -1.810$, $p < 0.10$). This leads to a weakly significant increase for consumers to receive a correct signal but only in a market without price competition (MWU: $z = -1.676$, $p < 0.10$). With price competition, this probability also increases, albeit with no significance (MWU: $p > 0.15$).

Table 4: Overview results across treatments

	FixLow	*FlexLow*	*FixHigh*	*FlexHigh*
Expert behavior				
z: Prob. correct signal	73.75% (.068)^{cq}	66.78% (.085)^{c}	78.90% (.071)^{q}	72.74% (.111)
x_h: High effort high skilled	44.55% (.263)	33.03 %(.330)^{q}	57.07% (.174)	50.37% (.201)^{q}
x_l: High effort low skilled	74.24% (.061)^{cq}	66.87% (.102)^{c}	80.00% (.240)^{q}	65.42% (.306)
d: Signal price	2	2.82 (.937)	2	2.96 (1.26)
p: Service price	5	4.03 (.557)	5	3.43 (1.39)
Consumer behavior				
f: Buy after first signal	13.79% (.134)	23.33% (.239)	16.36% (.177)	29.86% (.209)
$1-f$: Matching signals	67.88% (.175)	66.67% (.231)	74.55% (.188)	63.19% (.183)
Rational strategies	81.67% (.154)^{q}	90.00% (.096)	90.90% (.145)^{q}	93.06% (.054)
Leaving instantly	10.60% (.122)	5.60% (.072)	6.82% (.142)	4.03% (.053)
S: Visited experts	2.04 (.46)	2.18 (.62)	2.10 (.50)	2.01 (.39)
Market efficiency				
π_c: Consumer welfare	199.57 (24.15)	208.42 (40.25)	211.11 (18.39)	221.45 (44.07)
π_e^h: High skilled' profits	99.27 (30.60)	129.62 (52.92)^{q}	110.61 (21.28)	97.24 (26.99)^{q}
π_e^l: Low skilled' profits	103.00 (17.84)	97.33 (31.52)	113.36 (23.31)^{c}	84.94 (42.44)^{c}
π: Overall welfare	301.64 (24.13)^{q}	313.82 (23.04)	322.40 (23.99)^{q}	315.61 (19.61)
Solved problems	76.06% (.145)^{q}	81.67% (.133)	86.51% (.142)^{cq}	80.56% (.114)^{c}
Efficiency rate	81.01% (.065)^{q}	84.36% (.062)	86.67% (.065)^{q}	84.84% (.053)
Trade volume	81.67% (.154)^{q}	90.15% (.097)	91.06% (.143)^{q}	93.19% (.054)
Wrong Services	6.74% (.046)	9.88% (.075)	5.01% (.034)^{c}	13.76% (.098)^{c}
Number of Subjects	88	88	88	96

All given values are market averages across periods with clustered standard deviations in parentheses.
[q] Significant difference by qualification: *Low* vs. *High*($p < 0.10$).
[c] Significant difference by price competition: *Fix* vs. *Flex* ($p < 0.10$).

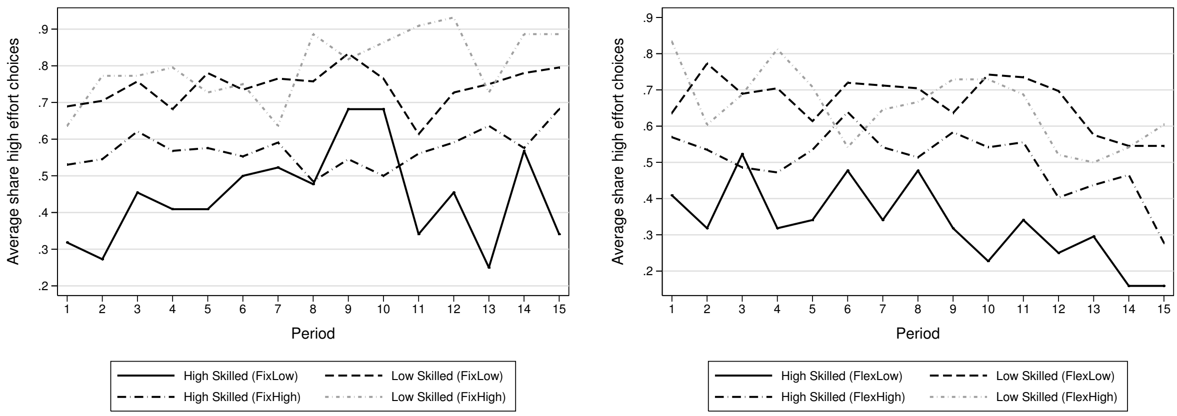
In Figure 5, we display expert behavior across all treatments. Without price competition, the expected increase in effort was 5%-points for high-skilled experts and 30% points for low-skilled experts, see Table 2. The actual increases are with 12.52% points for high-skilled experts significantly above (WSR: $z = 2.780$, $p < 0.01$) and with 5.76% points for low-skilled experts significantly below our predictions (WSR: $z = -4.211$, $p < 0.01$). In sum, high-skilled experts invest significantly more and low-skilled experts significantly less than we predicted in equilibrium (WSR: $p < 0.01$). However, if we take consumers' first-buy choices with $f = 0.167$ in *FixHigh* as given, experts' best response would be again to uniformly choose high effort with $x_h = 1$ and $x_l = 1$. Consequently, experts would be better off if they increased their high-effort choices even more. By testing for learning effects, it shows that low-skilled experts in *FixHigh* have a significantly higher probability of high effort in the last third of the experiment compared to the first third (WSR: $z = -2.408$, $p < 0.05$). By contrast, high-skilled experts show a weakly significant increase in investments from the second to the last third (WSR: $z = -1.824$,

$p < 0.10$). We do not observe the former effect from our baseline market for high-skilled experts of high effort rates rebounding.

With price competition, experts' best response depends on actual price levels. With 2.82 [2.96], the average price for a signal in *FlexLow* [*FlexHigh*] lies not only strictly above our prediction of $d = 0$ but also above the price in our reference markets without price competition. It is surprising that even though consumers would be strictly better off leaving the market without any action with an average price above 2.01 for a signal, the number of consumers actually choosing this strategy is the lowest with price competition. By contrast, with 4.03 [3.34], the average service price in *FlexLow* [*FlexHigh*] lies below our reference markets. We analyze experts' price setting behavior and the incidence that markets do not break down as expected in further detail in the next section and for now take it as given, since qualification has on average no significant effect on price setting (MWU: $p > 0.17$). Moreover, we take consumer behavior with $f = 0.233$ [$f = 0.299$] as given. In contrast to our treatments with fixed prices, with price competition the average service price p can fall below the critical threshold for experts to invest in high effort. This value is given by $p^l_{min} = 2$ for low-skilled experts and $p^h_{min} = 4$ for high-skilled experts. With average service prices remaining above the critical value for low-skilled experts in all periods, again they would be better off increasing their effort choices, given actual consumer behavior. This changes for high-skilled experts the moment when the service price falls below the critical value. From this point, it would be rational for high-skilled experts to always invest low effort, independently of actual consumer behavior. Looking at learning effects in a low qualified market, we observe a decrease in investments from the second to the last third for both low-skilled experts (WSR: $z = 2.405$, $p < 0.05$) as well as high-skilled experts (WSR: $z = 1.742$, $p < 0.10$). In a high-qualified market, we see a similar decrease in effort rates with low-skilled experts showing a weakly significant decrease from the first to the second (WSR: $z = 1.667$, $p < 0.10$) and high-skilled experts from the second to the last third (WSR: $z = 2.119$, $p < 0.05$). The formerly-identified effect of low-skilled experts investing less effort in sending their signals prevails in *FixHigh* and *FlexLow* but vanishes in *FlexHigh* (WSR: for *FlexLow* $z = -2.312$, $p < 0.05$; for *FixHigh* $z = -1.869$, $p < 0.10$; for *FlexHigh* $z = -1.177$, $p > 0.23$).

Consumer Behavior

In Figure 6, we show consumer behavior in all treatments. Without price competition, in *FixHigh* we predicted an almost 50% increase in consumers' search for matching pinions. While the actual increase is below our expectations, consumers still search more often for matching opinions than before, namely 74.55% of the time (WSR: $z = 2.046$, $p < 0.05$). The average share buying after their first signal remains almost unchanged with 16.36%, even though we predicted an almost 50% reduction, with this share still lying below our predictions (WSR: $z = -2.669$, $p < 0.01$). Nevertheless, the effect of expert qualification appears to reduce consumers' risk aversion, as they search less often for matching opinions and generally apply rational strategies more often. However, only the increased use of rational strategies to 90.00% is significant (MWU: $z = -2.127$, $p < 0.05$). Thereby, the share of consumers leaving without any action decreases to 6.82% and only 2.12% leave without buying a service. Again, consumers show on average no adaptation of their strategy across periods, with no differences between all thirds regarding f



(a) Fixed Prices

(b) Flexible Prices

Figure 5: Expert Behavior across Treatments

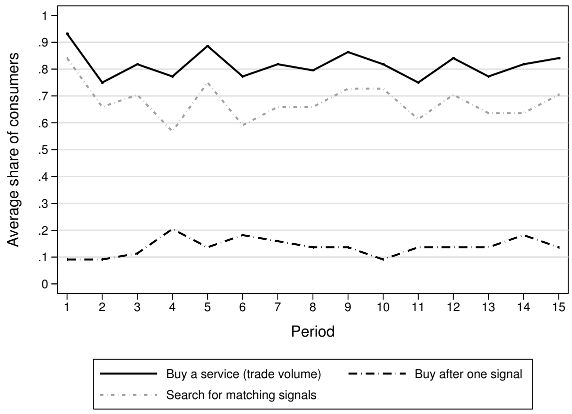
and $1 - f$ (WSRs: $p > 0.31$).

With price competition, our predictions depend on the actual chosen prices. If we assume the actual average prices as given, we would expect consumers to leave the market all the time without any action because signal prices are above the critical value to receive a positive expected payoff. Nevertheless, consumers still engage in trade. With expert qualification, consumers also generally buy more often after their first signal, although with flexible prices their share of searching for matching opinions is reduced. Additionally, the share of rational strategies increases on average, while the instant leavings are reduced, as well as the number of visited experts. However, these differences are not significant (MWUs: $p > 0.40$). In a low-qualified market, we see a significant increase in first-buy choices from the first to the second third, while at the same time searches for matching opinions decrease (WSRs: $p < 0.05$). In a high-qualified market, consumers show no learning effects (WSRs: $p > 0.17$).

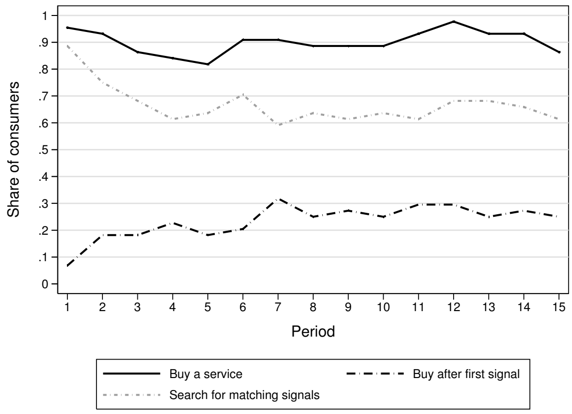
Market Efficiency

Without price competition, the volume of trade significantly increases to 91.06% of consumers buying a service (MWU: $z = -2.397$, $p < 0.05$). With a share of 86.51%, significantly more consumer problems are solved (MWU: $z = -2.007$, $p < 0.05$). This results from: (i) consumers reducing the use of non-rational strategies; (ii) the probability of a correct signal increasing; and (iii) the share of wrong services decreasing to 5.01%. However, aside from the reduction in non-rational strategies and the increase in the volume of trade, these changes are non-significant. Regarding the efficiency rate, we observe a significant increase to 86.67% (MWU: $z = -2.397$, $p < 0.05$), as consumers' welfare as well as high- and low-skilled experts' profits increase. This leads to a rejection of Hypothesis 2*c*.

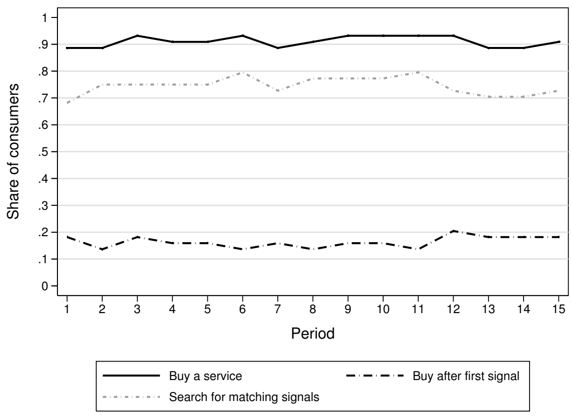
With price competition, while the volume of trade also increases to 93.19%, we see a reduction in the average number of solved problems to 80.56% which is mainly driven by an increase in wrong services to 13.76%. The changes are all non-significant (MWUs: $p > 0.24$). The efficiency rate remains almost unchanged at 80.56%. Regarding the individual welfare we see



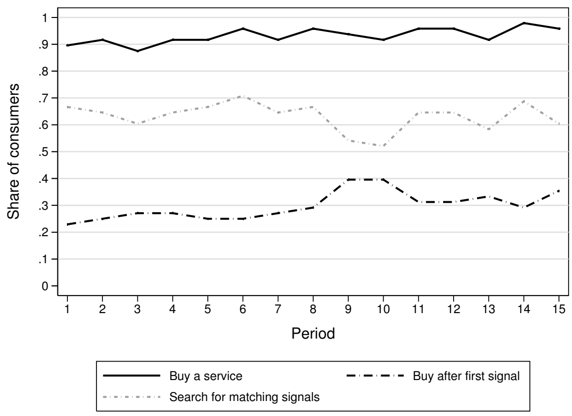
(a) FixLow



(b) FlexLow



(c) FixHigh



(d) FlexHigh

Figure 6: Consumer behvaior across treatments

a reduction in expert profits and an increase in consumer welfare. However, only the decrease in high-skilled experts' profits is weakly significant (MWU: $z = 1.662$, $p < 0.10$). This confirms Hypothesis 2e which predicted no influence of expert qualification with price competition.

Remarks: In sum, we see clear differences of expert qualification in markets concerning whether price competition exists or not. With fixed prices, expert qualification increases market efficiency significantly by higher probabilities of consumers receiving a correct signal and it also makes them less risk averse, as they apply rational strategies more often. Consequently, it appears worthwhile to qualify experts in markets without price competition. By contrast, with flexible prices the positive effects of expert qualification not only almost vanish but rather makes things worse, as efficiency decreases, albeit not significantly. However, keeping in mind that qualifying experts is expected to be costly, it seems unlikely that these investments would pay off.

5.4 Effects of Price Competition

Result 3 (Behavior and Efficiency according to Price Competition):

Experts: *Experts' investments decrease while remaining below their best response with fixed prices. With price competition, high-skilled experts invest too much and low-skilled experts too little, given actual prices and consumer behavior. These differences are mainly non-significant. The probability of a correct signal decreases in a low-qualified market but remains unaffected in a high-qualified market. Average prices for signals and services constantly decline over periods. While average signal prices are strictly above our predictions, service prices fall below the critical threshold for high-skilled experts with them still willing to invest in high effort. We observe no different average prices according to experts' types.*

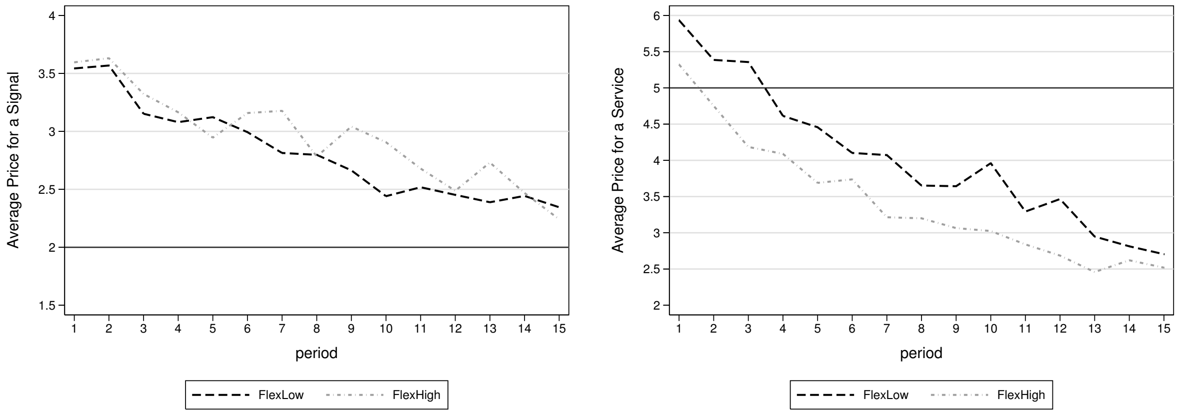
Consumers: *Markets do not break down and consumers even behave less risk averse with price competition while we observe no significant effects on consumers' search behavior and their share of applying rational strategies. In a high-qualified market, consumers increase their probability of buying after their first signal over time. On average, consumers do not adapt their search behavior according to service prices but are influenced by signal prices, i.e. having more trust in signals with higher prices.*

Market Efficiency: *In a low-qualified market, market efficiency increases non-significantly with a higher efficiency rate, more solved problems and higher volume of trade. In a high-qualified market, market efficiency decreases with a lower efficiency rate and significantly fewer solved problems. In general, welfare is shifted from experts to consumers with a significant decrease for low-skilled experts. For both markets, the share of wrong services increases.*

We analyze the effects of price competition in either a *Low* or *High* market. We separate the effects by comparing *FixLow* with *FlexLow* and *FixHigh* with *FlexHigh*.

Expert Behavior

We observe a decrease in experts' effort choices when prices are flexible. In a low-qualified market, low-skilled experts' investments significantly decrease (MWU: $z = 2.037$, $p < 0.05$). By contrast, high-skilled experts' decreasing investments in a low-qualified market as well as all experts' investments in a high-qualified market are not significant (MWUs: $p > 0.25$). We expected a decline in experts' effort choices, as only $\underline{z} = 0.03$ could be a potential equilibrium with consumers entering the market. It shows that z lies above this value in both market types (WSRs: $p < 0.01$). However, we observe a significant decrease in z by introducing price competition in a low-qualified market (MWU: $z = 1.972$, $p < 0.05$) but no effect in a high-qualified market (MWU: $p > 0.15$). We explain this by high-skilled experts in the latter reducing their effort not more intensively than their higher share in the market and their advantage in providing a correct diagnosis increasing the probability of a correct signal. In Figure 7, we present prices across periods for all treatments.



(a) FlexLow

(b) FlexHigh

Figure 7: Prices in *Flex*

We predicted that signal prices will be zero according to the standard Bertrand-argumentation. The actual chosen average price is not only strictly above zero but with 2.82 [2.96] in *FlexLow* [*FlexHigh*] it is also higher than with fixed prices. Consequently, we have to reject Hypothesis 3a. By contrast, with 4.03 [3.43] in *FlexLow* [*FlexHigh*], service prices are on average lower than without price competition. However, we can observe a steady decline in prices for signals as well as services over time. Signal prices fall by approximately 21% [19%] on average in the second half. The decline for service prices undergoes an even more drastic decline with approximately 32% [32%] in the second half.

In both treatments with price competition the average service price falls below $p^h_{min} = 4$ while high-skilled experts are still willing to choose $x_h > 0$, i.e. with a share of 33.03% [50.37%]. Instead, it would be more profitable for them to reduce their share of high effort to zero. Notice that this does not account for low-skilled experts, since over the whole course of our experiment, the average service price remains above their minimum price level $p_{min} = 2$. For low-skilled experts it would be more profitable to increase their effort investments also with price competition, instead of reducing it, given actual consumer behavior.

By comparing the price setting by experts of different types, we can confirm Hypothesis 3d. We see almost no significant differences for service or signal prices in *FlexLow* (WSR: $p > 0.37$) and only weakly significant results in a high-qualified market with high-skilled experts choosing weakly higher signal prices than low-skilled experts (WSR: $z = 1.647$, $p = 0.0995$).

Consumer Behavior

In sum, we see no significant differences in consumer behavior according to price competition in a low- as well as a high-qualified market. While we observe an increase in consumers' choice for rational strategies by introducing flexible prices, these changes are not significant regarding the probabilities of buying after one signal or after matching signals (MWUs: $p > 0.13$). In line with this, the accumulated probability of rational strategies and the share of consumers leaving without any action are not significantly different with flexible prices (MWUs: $p > 0.14$).

However, it appears that on average consumers behave less risk averse with flexible prices by increasing their first-buy choices, their choices for rational strategies and reducing their leavings without any actions.
According to the described learning effects in the former subsection, this contradicts Hypothesis $3f$, as we expected a strong correlation of f and p. While p is constantly falling on average, f remains almost unchanged across periods, resulting in a correlation coefficient with p of 0.040 [-0.055] in *FlexLow* [*FlexHigh*]. Instead, we find that consumers are more influenced by signal prices d with a correlation coefficient with f of -0.187 [-0.193] in *FlexLow* [*FlexHigh*]. We will analyze this in further detail in the next section.

Market Efficiency
In the low-qualified market, consumer welfare and high-skilled experts' profits increase but low-skilled experts' profits are reduced. Overall welfare increases as well as the share of solved problems, the volume of trade and the efficiency rate. However, none of these effects is significant (MWUs: $p > 0.17$). In the high-qualified market, consumer welfare also increases, while experts' profits shrink independent of their type as well as overall welfare. Moreover, the share of solved problem is reduced and the market arrives at a lower efficiency rate while the volume of trade increases. The reduction in low-skilled experts' profits and the share of solved problems is weakly significant (MWUss: $p < 0.10$).

Remarks: Summing up the results, we can confirm the results of Dulleck et al. (2011), namely that price competition reduces prices and increases the volume of trade, independent whether a market is low or high qualified. In contrast to Huck et al. (2012), while also increasing it, this has no significant effect on the market efficiency in our set-up. It appears that competition also increases consumer trust in our experiment by price competition, as consumers buy more often after their first signal. Additionally, while we can observe that welfare is redistributed from experts to consumers, with consumer welfare increasing on average with price competition, these effects are non-significant in contrast to Mimra et al. (2016a). In detail, we see different effects of price competition in a high- and a low-qualified market. In a low-qualified market, we observe a significant reduction in the probability of a correct signal, even though this does not have a significant influence on market efficiency, prices and consumer behavior. By contrast, these effects vanish in a high-qualified market but here consumers increase their probability of buying after their first recommendation over time. In general, we observe consumers' tendency to trust more expensive signals, since they buy after their first signal more often if signal prices are higher on average. This does not account for service prices, as we cannot find any relation between p and f. Regarding subject behavior, we observe clear deviations from our theoretical predictions and their best responses. Consumers participate in the market even though it would be theoretically more profitable for them to leave without any action. However, while they still act too risk averse given experts' actual effort choices, high-skilled experts invest too much effort given actual average service prices. By contrast, low-skilled experts invest less effort than it would be optimal which counterbalances high-skilled experts' low rates. While it might be worthwhile introducing price competition in a low-qualified market according to its efficiency-enhancing effect and particularly with its increasing effect on consumer welfare, our results indicate a negative influence of price competition in a high-qualified market.

5.5 Estimating the Effects of Qualification and Competition

In this section, we use parametric tests to investigate subjects' behavior in further detail. In Table 5 we present the coefficients from our random-effects regressions. We use panel tobit regressions to estimate the impact of competition, expert qualification, prices and specific consumer and expert behavior traits on the share of high-effort choices for experts, the probability to receive a correct signal from a random expert, the profits for experts and consumer welfare. Additionally, we use a panel probit regression to estimate the impact of the independent variables on whether consumers buy after their first signal.

In the first two columns, we estimate the likelihood of experts investing in high effort and providing a correct signal. Framing the probability for consumers to receive a correct signal the other way around, we receive the probability of consumers being undertreated, as a wrong signal cannot solve a problem if a service is conducted on it. Regarding our main treatment effects, we can confirm the formerly-identified positive influence of expert qualification on individual experts' high-effort choices. Additionally, experts are significantly more likely to invest in high effort the higher their individual chosen prices for signals and services. They are positively influenced by service prices and the number of services sold in the former period. It seems that experts experience some kind of obligation to invest more effort in their signals by higher prices and when consumers trusted them before. We confirm that high qualification has a strong negative effect on experts' high-effort choices. Additionally, females are significantly less likely to invest high effort.

Table 5: Random Effects Panel Tobit/Probit Regressions using Data from all Treatments

Independent variables	Share high effort	Prob. correct signal	Expert Profits	First signal buy (Probit)	Consumer welfare
Competition	-.191	-.067***	.415	.257	.849*
Expert Qualification	.496**	.052***	.295	-.120	.988**
Comp. x Qual.	-.092	.007***	-.1229*	.617	-.265
Own signal price	.163***		-.881***		
Own service price	.075***		-.892***		
Average signal price in t		.002	1.262***	.281***	-.998***
Average service price in t		.004***	1.374***	-.012	-.637***
Average signal price in t_{-1}	.026	.002	.092	.007	-.036
Average service price in t_{-1}	.065*	.005***	-.067	-.028	.321*
Number sent signals in t_{-1}	-.034		.175*		
Number provided services in t_{-1}	.145***		.141		
Wrong service in t_{-1}				-.332**	.034
High qualification	-1.084***		.496		
Share high effort			.227		
First signal buy					2.502***
Period	.008	-.002***	-.030	.044***	.039
Female	-.284*		-.981***	-.236	-.549*
Constant	.151	.701***	3.455***	-2.388***	16.508***
Observations	2,520	2,520	2,520	2,245	2,245

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

At the market level, we can confirm the influence of our main treatment effects, with competition significantly reducing the probability of consumers receiving a correct signal from a random expert. By contrast, expert qualification and the interaction of qualification and competition significantly increases this probability. In contrast to service prices, which have a positive influence, average signal prices in a market have no effect on the probability of a correct signal. Aggregated expert profits are unaffected by our main treatment effects, i.e. competition and expert qualification are non-significant. However, the interaction of competition and qualification has a weak negative effect on profits. Nonetheless, we observe a strong influence of prices. While the prices set by individuals have a strong negative influence, average prices in a market positively affect profits. This confirms the theoretical results from (Pesendorfer, Wolinsky, 2003) with experts' incentive to free-ride on others' choices by undercutting their prices. Experts profit from weak competition with high average prices in a market, as they can stand out with slightly lower prices and attract more consumers. We observe no significant influence of high-effort choices, which can be explained by contradicting influences depending on expert types. In contrast to our theoretical predictions, we find no differences according to experts' skill on their profits.

In the forth column, we use a probit model to estimate the influence of our independent variables on whether consumers buy after their first signal, which is an indicator of consumers' risk aversion. We cannot identify an influence of our main treatment effects with competition, qualification as well as the interaction term being non-significant. Confirming our former results, we see a strong positive influence of average signal prices on first-buy choices, which appears irrational as there is no such effect on the probability of receiving a correct signal. In case consumers have bought a service based on a wrong signal, this reduces their trust and their first-buy choices. It is surprising that we see a significant positive effect of period. Our results show that the probability to receive a correct signal from a random expert decreases with time and makes it less worthwhile buying without confirmation. This can be explained by consumers generally acting risk averse with first-buy-choices far below their best response, given expert behavior. Over time, consumers appear to learn at the individual level about experts' higher than optimal investments in high effort and begin to trust more, even though we cannot not find such an effect with our non-parametric tests. On the other hand, we observe no such learning effects on the expert side, as prices decline over time. Decreasing prices on the one hand and learning about consumers' risk behavior on the other might counterbalance each other, driving the effect of period to non-significance.

Finally, looking at consumer welfare, we observe a significant positive effect of competition and expert qualification. Additionally, it is unsurprising that the average prices of signals and services reduce consumer welfare. We can confirm our former statements of consumers buying less often after their first signal compared with their optimal response, since their welfare strongly increases with first-buy-choices. Again, we observe weakly significant less welfare for females.

6 Discussion and Conclusion

In this paper, we have experimentally analyzed expert and consumer behavior in a market for credence goods in which experts have a moral hazard problem in providing truthful diagnosis. Experts have to invest in costly but unobservable diagnostic effort to send true signals to consumers, which are necessary to solve consumer problems by an appropriate service. To our best knowledge, we are the first to provide an experimental design to investigate moral hazard in a market for credence goods. We built our four treatment conditions on our theoretical model from Schneider, Bizer (2017) which expands the framework of Pesendorfer, Wolinsky (2003). We introduced heterogeneously-qualified experts regarding their required effort to provide correct diagnoses with high-skilled experts having an advantage, as they need less effort to send a correct signal. We implemented a classical $2x2$ design by varying the share of high-skilled experts in the market and whether price competition existed. Besides looking at experts' high-effort choices and consumers' search behavior, we investigated how markets reacted and used four indicators for efficiency, i.e. the volume of trade, share of at maximum realized welfare, solved problems and the share of conducted wrong services.

In our baseline condition, the share of high-skilled experts was relatively low and prices were fixed. We investigated average market behavior and market efficiency according to the existing moral hazard problem in diagnosis and predicted the outcome based on our theory. We observed a significantly higher investment rate in experts' signals than we had expected, resulting in a relatively high probability of consumers receiving a correct signal. However, consumers acted risk averse by buying much less often after their first signal than expected and they mainly relied on the strategy of searching for matching signals. Additionally, a considerable share of consumers left the market without any action. Taking the actual results as given rather than comparing them with theoretical predictions, both sides could have improved their welfare, if they had adapted their strategies according to the other side's actual behavior. Given experts' high-effort investments, consumers could have improved by buying more often after their first signal, since the probability of receiving a correct signal was clearly above our predictions. Given consumers' risk aversion and their frequent search for matching opinions, experts could have increased their profits by higher investments in high effort. With low-skilled experts investing significantly more in high effort than high-skilled experts, which even counterbalanced their disadvantage in providing a correct diagnosis, they profited predominately from consumers' higher search rates. To our surprise, the market efficiency was significantly higher for all defined indicators than we had predicted. The higher search rates imposed overall welfare losses from more transaction costs. This was counterbalanced by the low share of wrong services, which was significantly below our prediction. According to our design, a wrong service imposes a welfare loss several times higher than the search costs for visiting another expert. We observed learning effects only for high-skilled experts with an increase in investments from the first to the second third. However, these higher investments rebounded in the last third almost back to the initial average. In sum, our baseline market was much more efficient than our theory had predicted but with potential for improvements as a considerable share of consumers distrusted the market and left without any action.

In the next step, we investigated how expert qualification affects outcomes in a market with or without price competition. We defined expert qualification as an increased share of high-skilled experts in the market. We observed a clear difference when experts were able to choose their prices on their own. Without price competition, experts' investments in their signals increased as theory predicted. This raised the probability of consumers receiving a correct signal. Consumers reacted by applying rational strategies, i.e. buying after their first signal and searching for matching opinions, more often and they left the market less often without any action. We saw a significantly positive effect on all efficiency indicators except for the share of wrong services, whereby this share even decreased. It is noteworthy that all experts' profits as well as consumer welfare increased on average by expert qualification and fixed prices. Nevertheless, the formerly-identified patterns prevailed, with consumers acting more risk averse than their best response would be given expert behavior, and experts investing too little effort given that consumers predominately search for matching opinions. With price competition, the positive effects of expert qualification not only almost disappeared but seemed to become negative. The only significant effect was for high-skilled experts, as they invested more effort, which reduced their profits, since they would do best with zero investments. While this appears to contradict our former descriptions of experts investing less effort than their best response would be, given consumer behavior, with flexible prices this turns around for high-skilled experts. Price competition constantly drives down prices for signals and services. For high-skilled experts, this becomes critical, as service prices quickly fell below their minimum price at which they should rationally invest in high effort. By increasing their high effort rates according to expert qualification while prices were falling, high-skilled experts profits were reduced. Despite being non-significant, expert qualification with flexible prices seems to have a positive impact for consumers. They behaved less risk averse with higher purchasing rates after their first signal and the lowest leaving rates without any action across all treatments. Moreover, welfare was redistributed from the expert side to consumers, whereby even the share of wrong treatments increased. In sum, expert qualification appears to have fundamentally different effects concerning whether price competition exists in a market. With fixed prices, efficiency was increased while qualification seems to have had rather negative impacts with flexible prices.

Finally, we isolated the influence of price competition in either a low- or a high-qualified market regarding the existing share of high-skilled experts. Most notably, in contrast to our predictions, markets did not break down by consumers leaving without any action all of the time. Price competition reduced experts' investments in both markets. This reduced the average probability of a correct signal. At the same time, consumers appeared to trust more with a higher probability of buying after their first signal and less leavings without any action, which seems to confirm the results of Huck et al. (2012). This is also in line with the presented JAS-literature, since flexible prices imply higher degrees of freedom, which seems to be interpreted by consumer as being more trustworthy. However, according to the tendency of consumers to trust high costly signals more, higher trust rates might have simply resulted from higher signal prices with flexible prices rather than the effect of competition between experts per se. It seems that price competition had positive effects on the market efficiency, albeit only in a low-qualified market, with higher welfare for consumers and high-skilled experts, more solved problems and a higher volume of trade. However, all of these effects were non-significant. In a high-qualified market, price competition shifted experts profits to consumers but reduced market efficiency with significantly fewer solved problems and a higher share of wrong services. In line with the existing literature, e.g. Dulleck et al. (2011) and (Mimra et al., 2016a), prices for signals and services declined over periods in both markets and the volume of trade increased. However, it is surprising that signal prices were on average strictly above not only our prediction of being zero but also above our reference values with fixed prices. By contrast, service prices quickly fell below the reference value and even under the critical threshold for high skilled experts while they were still willing to invest in high effort. We did not identify any real differences in price setting neither concerning whether a market was high or low qualified nor for whether individual experts were high or low skilled. In sum, we could not confirm the efficiency-increasing effect of price competition from the literature, irrespective of whether we consider a low- or high-qualified market.

Being the first to provide an experimental design investigating moral hazard in experts' diagnosis in a market for credence goods, we provide a basis for further research. While we have been able to investigate a variety of factors and their effects on expert and consumer behavior as well as on market efficiency, our model and experimental design made several restricting assumptions. We assumed that there is only one possible service that solves a consumer's problem. Regarding the existing literature, it would be more realistic to differentiate between potential over- and undertreatment with varying payoff options. Furthermore, we only examined how a varying share of high-skilled experts affects the outcome but let their advantage in diagnosis remain fixed across treatments. It would be interesting how subjects behave to different degrees of qualification and whether different investments of high- and low-skilled experts prevail.

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Appendix A - Instructions

General Information to the Experiment

In this experiment, there will be groups of eight players with no interaction between different groups. Each group comprises four players of type A and four players of type B. At the beginning of the experiment, it will be randomly determined whether you are assigned the role of player A or player B. Groups and role allocation will remain unchanged over the whole experiment. The experiment has 15 periods.

In the experiment, each player B has a **problem**. This will be presented as a numeric value between 0 and 1 (with two decimal places), e.g. 0.12. To solve a problem players B have to visit one or more players A to receive **signals** about their problem and conduct a **service**. Each signal is also presented as a numeric value between 0 and 1 (with two decimal places). A signal can be correct or wrong. If a signal is correct, its value and the value of the corresponding problem are identical. If a signal is wrong, the two values differ. The players B cannot identify whether a signal is correct or wrong. Each player B can receive up to four signals (maximal one from each player A). To solve their problems, players B have to purchase a **service** from a player A that is based on a correct **signal**.

Each player A decides [T1/T3: which prices he demands for sending a signal and for a service in this period and] how he wants to treat each single player B in case she visits him. The players A can always choose between **two actions** which automatically result in either a correct or a wrong signal is being sent to a player B.

Your income in this game depends on your decisions and those of the other players in your group. You income will be calculated in coins with **1 coin = 5 cent**. At the end of each period, you will be informed about your income for the current period and how much you have earned across all periods. At the end of the game, your payoff will be transferred from coins into Euros (rounded up to one decimal place).

The Course of the Game

The experiment has **15 periods**. Each period has an identical course:

1. [T1/T3: Each player A decides which prices he demands in this period for sending a signal and a service.]
2. Each player A decides for each single player B which action he wants to carry out in case this player visits him.
3. Each player B decides whether and how many players A she wants to visit for a signal and whether she wants to purchase a service. [T1/T3: During this stage, each player A observe which prices have been chosen by the other players A in this period.]
4. Decisions are implemented.
5. All players are informed about their decisions and their payoff in the current period.

In the following, the course and the different options for each player will be explained in detail.

The Role of Player A

[T1/T3: At the beginning of each period as a player A, you decide which price (from 0 to 15) you demand from the players B for sending a signal and a service. The players B have to pay an additional fee of 0.2 coins on top of your price for sending a signal. For conducting a treatment there will be no fee.]

At the beginning of the experiment, each player A receives either the attribute 1 or the attribute 2. The allocated attribute influences the consequences of your actions as a player A (see below) and does not change during the experiment. **In each group, 1 player receives the attribute 1 and 3 players receives the attribute 2. [T2/T3: In each group, 3 players receive the attribute 1 and 1 player receives the attribute 2.** At the beginning of the experiment, all players A are informed about their individual attribute.

In each period, you decide as a player A how you want to treat each single player B. You decide upfront for the case that a player B actually visits you for a signal. In sum, you have to make four decisions in each period at this stage. A decision will only be implemented, if the corresponding player B actually visits you.

For each player B, you always have two actions to choose from:

- If you choose **action 1**, this will cost you 1 coin and you will send the correct value of this player B's problem to her.
- If you choose **action 2**, this will cost you 0 coins. The consequences in this case will depend on your attribute:
  - o With **attribute 1** you will send with 50% probability the correct value and with 50% probability a wrong value to this player B (see first table).
  - o With **attribute 2** you will send a wrong value to this player B (see second table).

Actions and consequences as player A with **attribute 1** (3 [1] player[s] from each group receive this attribute)

Selection	Consequences
Action 1	Choosing action 1 will cost you 1 coin. You will send the correct value to this player B, if she visits you.
Action 2	Choosing action 2 will cost you 0 coins. You will send with 50% probability the correct value, and with 50% probability a wrong value to this player B, if she visits you.

Actions and consequences as player A with **attribute 2** (1 [3] player[s] from each group receive this attribute)

Selection	Consequences
Action 1	Choosing action 1 will cost you 1 coin. You will send the correct value to this player B, if she visits you.
Action 2	Choosing action 2 will cost you 1 coin. You will send a wrong value to this player B, if she visits you.

For each player B who visits you for a signal, you receive the payment of 2 coins [T1/T3: your determined price for sending a signal.] If you have chosen action 1 for this player B, 1 coin will be subtracted from this. Notice that your decisions are only implemented, if a corresponding player B actually visits you. Consequently, you will only have the 1 coin subtracted by the choice of action 1, if a player B actually visits you.

Example: In a given period, a player B has the problem with the value 0.12. Assuming that you are player A with attribute 2 [T1/T3: , have chosen the price of 2 coins for sending a signal] and this player B is going to visit you. If you choose action 1, you receive 1 coin (2 coins - 1 coin) and send the signal 0.12 to this player B. If you choose action 2, you receive 2 coins (2 coins - 0 coins) and send a random but definitely wrong value, e.g. 0.76, to this player B.

The players B cannot identify which player A sends them a signal, which attribute a player A was allocated and whether the sent signal is correct or wrong.

After player B receives a signal from you, she can purchase a service for the price of 5 coins [T1/T3: for the price you have determined at the beginning of the period]. Notice that sending a signal does not imply the automatic purchase of a service. Each player B can choose freely between all players A who she has visited for a signal in a given period (see *The Role of Player B* for more details).

Subsequently, we present the decision screen for player A. **Notice that the presentation of the players B in the columns will be randomly determined in each period.** Consequently, you do not know which player B is presented in which column.

[Decision Screen players A]

<u>Summary payoff options for player A:</u>

The following payoffs refer to a single player B. You payoff **in a given period** is the **sum of payoffs from all four players B**

- **For each player B who visits you and purchases a service, you receive:** Payoff = 5 coins (price service) + 2 coins (price signal) - 1 coin (if you have chosen action 1) [T1/T3: Payoff = price service + price sending signal - 1 coin (if you have chosen action 1)
- **For each player B who visits you but does <u>not</u> purchases a service, you receive:** Payoff = 2 coins (price signal) - 1 coin (if you have chosen action 1) [T1/T3: Payoff = price sending signal - 1 coin (if you have chosen action 1)
- **If a player B does <u>not</u> visit you, you do not receive any payoff from her in this period, but you also do not have any subtractions by choosing action 1 for her.**

At the end of the experiment, each player A receives a show-up fee of 7 Euro. This will be added to your payoff on the final screen.

<u>Example of player A's payoff in a given period:</u>
You are player A and [T1/T3: decides to set the price for sending a signal at 2 coins and for conducting a service at 5 coins. You] choose the following actions for the players B in your market:

Player	**Your decision as player A**
First player B	Action 1
Second player B	Action 1
Third player B	Action 2
Fourth player B	Action 1

Assuming that the first, third and fourth player B visit you for a signal and that the first player B purchases a service from you. You receive a payoff of 9 coins in this period. This results as follows:

Player	**Payoff from this player in this period**
First player B	6 coins = 5 coins (service) + 2 coins (signal) - 1 coin (action 1)
Second player B	0 coins (no visit; therefore no subtraction from choosing action 1)
Third player B	2 coins (signal)
Fourth player B	1 coin = 2 coins (signal) - 1 coin (action 1)
Final profit this period	**9 coins** = 6 coins + 0 coins + 2 coins + 1 coin

The Role of Player B

In every period, each player B has a new problem which is presented as a random numeric value between 0 and 1 (with two decimal spots), e.g. 0.12. **This is randomly determined in each period.** You will never be informed about the actual value of your problem. Your problem will be solved, if you purchase a service that is based on a correct signal only. **If your problem is solved, you receive an additional payoff of 13 coins.**
At the beginning of each period as a player B, you receive an endowment of 12 coins. You have to decide whether and how many players A you want to visit for a signal. Additionally, you have to decide whether you want to purchase a service from a player A that is based on a formerly received signal. Each received signal from a player A is also presented as a numeric value between 0 and 1 (with two decimal spots). This value only equals your problem's value in a given period, if the signal is correct (see *The Role of Player A* for more details). **If you receive two signals with identical values you can be sure that both signals are correct.**

In each period, you can choose between the following actions:

- Visit a (new) player A (costs 2,2 coins [T1/T3: costs depending on chosen prices]):
  You can visit a (new) player A to receive a signal. This will cost you 2,2 coins. [T1/T3: The costs depend on the prices chosen by the different players A in this period.] You can visit each player A only once. Notice that the presentation of the players A on your screen is randomly determined in each period. Consequently, you cannot identify which player A is presented in which column.
- Purchase a service (costs 5 coins [T1/T3: costs depending on chosen prices]; ends the period):
  Based on a formerly-received signal, you can purchase a service from this player A. This costs you 5 coins. [T1/T3: The costs depend on the price chosen by the different players A in this period.] This action ends the period. You can choose freely from all signals that you have received in this period. This action is only available, if you have received at least one signal. If the signal on which you purchase a service is correct, you receive an additional payoff of 13 coins. If the signal is wrong, you receive no additional coins.
- End the period (ends the period, all incurred costs remain valid):
  You can end a period without receiving a signal and/or purchasing a service. All incurred costs will remain valid (e.g. if you have visited three players A for a signal for the price of 2,2 coins each, and you end the period without purchasing a service, you have 6.6 coins deducted from your endowment).

Subsequently, we present the decision screen of player B:

[Decision Screen players B]

Summary payoff options for player B:

- **If you purchase a service and the corresponding signal has been correct:**
  Payoff = 13 coins (solved problem) + 12 coins (endowment) - 5 coins (price service) - 2.2 ∗ number visited player A [T1/T3: Payoff = 13 coins (solved problem) + 12 coins (endowment) - price service - costs of all received signals]
- **If you purchase a service and the corresponding signal has not been correct:**
  Payoff = 12 coins (endowment) - 5 coins (price service) - 2.2 ∗ number visited player A [T1/T3: Payoff = 12 coins (endowment) - price service - costs of all received signals]
- **If you do not purchase a service:**
  Payoff = 12 coins (endowment) - 2.2 ∗ number visited player A [T1/T3: Payoff = 12 coins (endowment) - costs of all received signals]

Example: You are player B and visit two players A for a signal. [T1/T3: Assuming that both players A have chosen identical prices for sending a signal (2 coins) and for a service (5 coins).] Notice that as a player B you have to pay an additional fee of 0.2 per received signal. Assuming that you decide to purchase a service from one of the visited players A:

- If this player A's signal was correct, you receive a payoff of 15.6 coins (= 13 coins + 12 coins - 5 coins - 2.2 coins ∗ 2).
- If this player A's signal was <u>not</u> correct, you receive a payoff of 2.6 coins (= 12 coins - 5 coins - 2.2 ∗ 2).