Determinants of Human Cooperation

About the Influence of Moral Balancing, Group Identity, Competition, Consumer Information & Expert Qualification

Dissertation

zur Erlangung des Doktorgrades
der Wirtschaftswissenschaftlichen Fakultät
der Georg-August-Universität Göttingen

vorgelegt von

Tim Arne Schneider

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Chapter 1

INTRODUCTION AND SUMMARY

"Ants and bees can also work together in huge numbers, but they do so in a very rigid manner and only with close relatives. Wolves and chimpanzees cooperate far more flexibly than ants, but they can do so only with small numbers of other individuals that they know intimately. Sapiens can cooperate in extremely flexible ways with countless numbers of strangers. That's why Sapiens rule the world, whereas ants eat our leftovers and chimps are locked up in zoos and research laboratories." Harari (2015)

Even though it is difficult to prove that it has been large-scale cooperation[1] that actually cleared our path, and its primary role for our development as the dominant species might be denied, there should be no argument about its relevance for our today's living. We all constantly engage in cooperative behavior in business as well as private interactions, placing trust in others or simply engaging in voluntary actions that reduce our monetary earnings while increasing payoffs for others (Burnham, Hare, 2007). Whether on a small scale like within families or working teams or on a larger scale such as within organizations or nations, we are all continuously confronted with dilemma situations where it might be individually more profitable to defect or cheat rather than cooperate. However, with our inability to make perfect contracts, we all depend and rely to some degree on others' willingness to cooperate.

According to Darwin (2006), humans, like all animals, strive for the survival of the fittest. Accordingly, why should we ever engage in cooperation with potential competitors when being a nice guy merely implies "an individual that assists other members of its species, at its own expense, to pass their genes on to the next generation." (Dawkins, 2006)? In the literature, a variety of theories exist concerning why cooperation is generally sustainable, even in a competitive environment: e.g. inclusive fitness theory, which is also known as kin selection (Hamilton, 1964; Foster et al., 2006); reciprocal altruism (Trivers, 1971; Fehr et al., 2002; Bowles, Gintis, 2003); or the evolution of social norms (Pillutla, Chen, 1999; Fehr, Fischbacher, 2004; Burnham, Hare, 2007). While also being quite interesting, I do not primarily seek to answer the question of why humans engage in cooperative behavior generally in this book, but rather focus on what influences whether and to what degree humans cooperate in a given situation. While these two questions cannot be clearly separated from each other, knowing more about the triggers and blockers of cooperation in given situations allows outlining more efficient conditions for e.g. policy-makers or companies to foster cooperation.

Humans are complex creatures and our decisions to cooperate or defect depend on a magnitude of relevant factors. I will classify these factors as being either internal or external. As internal

[1]By cooperation, I will stick to the notion of Bowles, Gintis (2003) and understand it as an individual's willingness to incur personal costs or renounce additional profits to enable a joint activity from which another individual or a group as a whole benefits.

factors, I will describe all influences that originate from within an individual's organism, e.g. emotions, affiliation, gender, moral values or identities. By contrast, I define factors as external that are imposed on an individual, e.g. situation-related context, institutions or others' behavior. I am aware that determining something's origin as internal, e.g. like moral values, might rather be determined by external factors like culture or nurture. For simplification, I will rely my classification on the moment when an individual actually makes a decision and consequently whether or not a factor is externally imposed at this very moment. Of course, all presented factors should not be taken as independent but as more or less interacting (Sakamoto et al., 2013).

Internal Factors for Human Cooperation

In economic standard theory, it is commonly accepted that individuals choose an action when its expected benefits exceed its expected costs. Furthermore, it is assumed that the act of lying per se is without any costs and only monetary factors are taken into considerations (Gneezy, 2005). This would imply that when faced with the decision of being dishonest, individuals simply weight the pecuniary advantages and disadvantages, subsequently make a conclusion and act accordingly (Gravert, 2013). However, experimental evidence contradicts this pure focus on monetary incentives, given that individuals also recognize non-pecuniary incentives such as feelings, complying with norms and their own self-image.

Individuals derive utility from a positive self-image, which they try to maintain at a satisfactory level (Akerlof, Kranton, 2000; Loewenstein, 2000; McLeish, Oxoby, 2007; Gino et al., 2011; Ploner, Regner, 2013). Such self-image, or rather an individual's sense of oneself, can be defined as an one's own identity. Through memberships in groups, individuals adapt behavioral traits that are somehow consistent with their ideals and try to live up to them (Benjamin et al., 2007; Akerlof, Kranton, 2008; Chen, Li, 2009). Konrath, Cheung (2013) and Cappelen et al. (2013) show that individuals' utilities from their self-image depend on such internalized norms because the willingness to cheat and whether such an act is perceived as a transgression depends on it (Pascual-Ezama et al., 2013). In general, individuals have the urge to conform to their social environment and act in accordance with its prescriptions (Thaler, Sunstein, 2009). Several experiments reveal the existence of such conformity pressure. In his famous setup, Asch (1955) show that people are willing to adapt obviously false opinions when confronted with the preceding wrong answers of others. The existence of self-fulfilling prophesies by confirmatory behavior is confirmed by Salganik, Watts (2008). In simulated music download portals, they reveal that individuals tend to prefer songs that are already most popular. Another example is the study of Milgram (1963) on obedience, showing that people are willing to cross their own moral boundaries by obeying instructions that they considered as important and socially

acknowledged.
In case people deviate in any direction from their optimal level of self-image, they engage in moral cleansing or moral licensing to reestablish it (Sachdeva et al., 2009; Brañas-Garza et al., 2013). Moral licensing occurs when an individual carries out good deeds, which gives her a superior self-image. Since individuals try to maintain their self-image at an optimal level rather than maximizing it, they tend to behave badly after they have boosted their self-image, having licensed themselves to disregard norms or codes of conduct. This argumentation is turned around for moral cleansing: assuming an individual violates social norms and experience a reduction in her self-image, to re-establish her self-image, she will engage in moral cleansing by behaving more morally she would otherwise do so (Ploner, Regner, 2013). Baumeister et al. (1994) determine guilt as the driving force behind moral balancing, resulting from the failure to live up to one's own and others' expectations or by violating social norms (Erat, Gneezy, 2012). Since moral balancing takes place even when nobody else is present, it is not a mere self-representational strategy (Merritt et al., 2010). Thereby, the whole process of moral balancing appears to be short-lived. Individuals forget about their good and bad deeds very quickly. If balancing does not take place in a contemporary way, it will not happen regardless (Brañas-Garza et al., 2013). Moreover, it appears that the costs of lying can be outsourced by delegation. Erat (2013) shows experimentally that subjects are significantly more likely to employ a third person for their 'dirty work' if deception would cause relatively greater harm.
Experiments show that some individuals have a strict lying averse attitude (Erat, Gneezy, 2012; Cappelen et al., 2013; Gneezy et al., 2013). They abstain strictly from deceiving another person, cheating in an interaction (Gneezy, 2005; Erat, 2013; Fosgaard et al., 2013; Gino et al., 2013; Gravert, 2013; Pascual-Ezama et al., 2013) or violating social norms (Servátka, 2010; Dreber et al., 2013; Herne et al., 2013), even when there is no risk of being caught or punished. This also accounts for Pareto white lies[2] and cannot be attached to egoistic motives per se. Consequently, some individuals perceive the act of lying as something strictly immoral and associate higher costs with it, which might even outbalance any pecuniary incentive.
Individuals' willingness to behave dishonestly is also influenced by their demographics. Here, the literature documents significant differences between men and women. For example, men are more likely to engage in deception that benefits themselves at the expense of others (Gneezy et al., 2013). Additionally, Erat, Gneezy (2012) show that women are on average significantly more likely to tell an altruistic white lie[3] but are more reluctant towards Pareto white lies. Moreover, Erat (2013) finds that women are more likely to use an agent to delegate the act of dishonesty which might reveal a greater sensitivity to the underlying costs. However, Cappelen et al. (2013) are unable to confirm these results in their experiment.

[2] A white lie is an action that violates a social norm but that enhances the overall welfare, while not making any involved individual worse off.
[3] An altruistic white lie reduces one's own payoff while enhancing another person's payoff.

Furthermore, physiological conditions influence the willingness or rather the capability to act honestly. Motivational conflicts seem to consume specific mental resources, identified as the moral muscle (Gino et al., 2011). The experiments of Gino et al. (2011) and Mead et al. (2009) suggest that the process of moral balancing depends on whether these mental resources have been used recently. In line with this, Fosgaard et al. (2013) conclude that the degree of intelligence is correlated with the likelihood that a person engages in dishonest actions. However, Cappelen et al. (2013) are unable to verify this relation as they do not find any significant differences to cognitive abilities.

External Factors for Human Cooperation

The social psychology literature reveals that the behavior of surrounding people crucially affects the honesty of individuals who generally tend to behave according to their group members' preceding actions (Fosgaard et al., 2013). Additionally, Gino et al. (2013) show that the group size as well as the possibility to interact with its members have a significantly positive effect on individuals' willingness to cheat. As communication increases the focus of prevalent norms and preceding actions within a group, this confirms the former statement that individuals adjust their behavior towards the most meaningful norms within a group (Dreber et al., 2013). By contrast, an increasing group size reduces the costs of deception because it reduces the personal accountability. Servátka (2010) verifies the general assumption that individuals tend to be nicer to nice people, which is confirmed by experimental studies showing that participants engage in strong reciprocal behavior (Fehr, Fischbacher, 2004; Herne et al., 2013).
Moreover, the decision concerning whether to behave dishonestly depends on the context and its associated expectations. Battigalli et al. (2013) use poker players as an illustration, given that they usually lie and bluff while playing. Within this context, nobody expects an opponent to tell the truth, but simultaneously nobody condemns anybody else for such a usually norm-violating behavior. Additionally, process satisfaction influences individuals' willingness to punish dishonest behavior. Brandts, Charness (2003) show that immoral acts are significantly less tolerated when deception have preceded: individuals are interested and sensitive towards potential first movers' choices, their foregone alternatives and whether an action was intended.
Besides the described non-monetary incentives, individuals also react to changing pecuniary incentives. In his experiment, Gneezy (2005) shows that the decision to deceive is influenced by relative gains and relative costs, although individuals take the payoff of all involved parties into consideration. This is confirmed by another experiment of Gneezy et al. (2013), concluding that lying increases with higher monetary gains.

Dishonest Behavior and Moral Cleansing

The first approach to investigate human cooperative behavior in general adds to the moral balancing theory and focuses on individuals' self-image, i.e. the identity that they derive from living up to expectations while minimizing group-level awareness. In "*The Victim Matters - Experimental Evidence on Lying, Moral Costs and Moral Cleansing*", we investigate experimentally moral cleansing, i.e. the tendency to behave more morally after bad deeds, in a setting with endogenous manipulation of subjects' moral self-image. We thus analyze the context dependence of moral cleansing by showing that the opportunity to cheat on individuals in different roles incurs different moral costs and leads to different degrees of cheating and moral cleansing. To investigate the impact of different addressees of an immoral action on moral cleansing, our experimental design builds closely on Ploner, Regner (2013). We investigate the extent of cheating and subsequent moral cleansing, whereby in two distinct treatments subjects know that cheating is conducted at the expense of either the experimenter or another subject. To enable an endogenous manipulation of their self-image, subjects' initial endowment is determined by self-reported hidden rolls of a fair die. False numbers can be reported to gain a higher payoff. Subsequently, subjects play a standard dictator game which gives the possibility to engage in moral cleansing by sharing their endowment with another subject.

We find that cheating the experimenter is widespread yet incurs little moral costs and apparently no reduction of the moral self-image; consequently, there is no substantial moral cleansing. Furthermore, no 'Robin-Hood-Effect' occurs, as cheating the experimenter is not associated with increased donations. By contrast, cheating at the expense of another subject halves the number of cheaters; obviously, a substantial share of subjects anticipates the moral costs and thus chooses not to cheat in the first place. Subjects who claim high endowments at the expense of another subject in turn donate significantly more, which should be interpreted as moral cleansing. Both reactions can be asserted through the moral self-image: as the moral costs of cheating on another subject are dealt with by either avoiding them ex ante or cleansing them ex post, the moral self-image is necessarily equal to that of our control group.

More generally, it can be stated that once moral costs are high, e.g. when an opportunity to cheat on another person is taken, both avoiding the immoral action and moral cleansing are likely to occur. By contrast, frequent rational cheating and little ensuing moral cleansing will occur when the addressee is a faceless organization only evoking minor social concerns, as is conceivable e.g. for large corporations or the state. Our results suggest that cheating the taxman would be considered morally acceptable to many more people and would not lead to the desire to share the profit to feel better rather than cheating a real person. Our results thus emphasize that moral balancing should not be seen as a stand-alone effect, but rather that its occurrence crucially depends on the addressee of immoral behavior. This could be crucial for the design of organizations that are characterized by a set of rules prone to cheating. Once individuals are given the opportunity to make profits by not adhering to (unenforced) rules, they will be more likely to engage in immoral behavior without feeling guilty when the victim is perceived to be an anonymous organization. Instead, if the organization credibly assigns the blame and punishment for losses incurred from cheating to a single person, rational cheating will be associated with substantially higher moral costs and will thus lead to the avoidance or – at least – compensation of immoral actions.

The Effect of Competition and Group Identity on Cooperation

In the first approach to investigate cooperative behavior, the focus lies on individual decision-making by excluding influences at the group level, i.e. subjects' decisions only affected their own payoff in the first stage and the matched subject's payoff in the dictator game: with the common anonymity protocol in economic experiments, subjects' awareness of their membership in groups is minimized. The second approach "*Cooperation in public goods games: Enhancing effects of group identity and competition*" explores individuals' identity from a different angle, investigating how group identity and competition within and between different groups affect cooperation.
Conflicts within and between groups are omnipresent in everyday life (Chowdhury et al., 2016) However, groups cannot be modeled as independent unitary actors, since sub-groups' and individuals' interests do not necessarily coincide. Consequently, individuals might be confronted with contradictory incentives for either defecting, i.e. maximizing their own payoff, or cooperating, i.e. maximizing the group's payoff. This becomes evident in public goods games with individuals' investments in public goods usually falling short of optimal amounts. Such intra-group conflicts rarely appear as isolated incidents because they are usually accompanied by inter-group competition, e.g. a team or company as an in-group competes for an exogenous prize with other teams or companies as out-groups. Like with intra-group competition, conflicting interests arise with inter-group competition, since individuals want to win the competed exogenous prize from the inter-group competition while they might also want to invest minimal resources and prefer to free-ride (Camerer et al., 2011; Fischbacher, Gächter, 2010).
We explore experimentally how increased group identity and varying distributive mechanisms for the exogenous prize affect individuals' willingness to cooperate in a setting with intra-group and inter-group competition. To model intra-group competition, we play a public goods game. The exogenous prize that we use to model inter-group competition, is distributed among the wining team's members with the size of a group's generated public good determining the probability of winning the prize. We use a standard 2x2 design by varying the level of

group identity and the prize distribution mechanism. To increase group identity, we apply the procedure from Eckel, Grossman (2005) by letting subjects solve a puzzle task in face-to-face interactions with their team members. To investigate how different monetary incentives influence individuals' cooperative behavior in our setting we either distribute the exogenous prize proportionally to an individual's investments in the public good or egalitarian among all members of the winning group.

Our results show that investments in public goods increase with higher levels of group identity. Moreover, subjects invest significantly more in the public good under the egalitarian profit-sharing rule with high group identity. This is surprising because it contradicts previous findings indicating stronger effects of the proportional profit-sharing rule. We explain this through subjects' inequity aversion (Fehr, Schmidt, 1999). Finally, the number of subjects who fully cooperate, i.e. invest their full endowment in the public good, is significantly higher when group identity is increased.

Summing up the results, it is shown that cooperative behavior can be described by three main factors: (i) increasing group identity and perceived in-group attachments positively affect the willingness to cooperate; (ii) contest situations (e.g. external monetary incentives) increase cooperation; and (iii) history matters, i.e. when group members experience a positive event within their group such as winning the prize or high investment by their peers, this subsequently increases individuals' willingness to cooperate.

To sum up the first part of this book, it becomes evident that human cooperation and cheating behavior is a complex mechanism depending on multiple internal and external factors. The authors show experimentally that individuals strongly care about how they perceive themselves, as well as how others judge them. Individuals constantly try to maintain a comfortable self-image. They increase cooperation due to moral balancing, if they behaved badly in the past, to recreate their optimal point of self-image. The same accounts for the case whereby their awareness of being a group member is enhanced. Moreover, being in competition with another group or being more involved in the expected profits also increases the willingness to cooperate.

Cooperation in Credence Goods Markets

I have presented literature and investigations about human cooperative behavior in general. The underlying studies are primarily based on classic economic games like the dictator game, the prisoner's dilemma or public goods games, for example. Despite being useful to derive general predictions about human behavior, they are often too stylized to enable implementable policy recommendations. Many economic interactions are based on more complex structures, meaning that more sophisticated models and experiments are necessary. An example of such a more complex interaction is markets for credence goods, which will be the focus of the second half of this book.

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, thus 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). Altogether, consumers are neither able to determine ex ante the best solution for their difficulties, i.e. which maximizes their payoff, nor identify ex post the exact treatment that relieved them. Consequently, experts might use their superior knowledge to cheat on consumers by overtreating, overcharging or undertreating them (Dulleck and Kerschbamer, 2006, 2009; Dulleck et al., 2011).

In general, consumer makes decisions based on formerly-acquired information from an expert. Here, I identify two critical factors in reference to the Judge-Advisor-System (JAS) literature: (1) what affects consumers' decisions to follow advice or trust experts; and (2) what affects experts' degree of cooperation of rather sincerity in their communication. It seems that consumers adjust their willingness to follow advice to the source and its identifiable characteristics (Bonaccio, Dalal, 2006; Eckerd, Hill, 2012; Mortimer, Pressey, 2013; Schotter, 2003; White, 2005). Consumers discount advice to different degrees, which is influenced by whether the advice has been liable to costs and when it was paid (Angelova, Regner, 2013; Gino, 2008). Thereby, discounting rates increase when experts' interests are divergent from consumers' interest and if advice is imposed. The way in which advice is transmitted also matters, with most following in face-to-face situations (Bonaccio, Dalal, 2006). However, consumers are not only more willing to follow advice in face-to-face situations, but experts are also more sincere in their communication, pointing to increased costs for lying in personal interactions. Regarding experts' willingness for sincere communication, Crawford, Sobel (1982) argue that until interests perfectly coincide signals will be noisy.

The term credence goods has been introduced by Darby, Karni (1973) in addition to search and experience goods. "Generally speaking, credence goods have the characteristic that though consumers can observe the utility they derive from the good ex post, they cannot judge whether the type or quality they have received is the ex ante needed one." (Dulleck et al., 2011). In the literature, it is usually assumed that consumers are homogenous and have only vague information about their problem at hand, but know that they suffer from either a minor or a serious problem with a commonly-known probability and need either a cheap or an expensive treatment (Wolinsky, 1993; Emons, 2001; Dulleck, Kerschbamer, 2006, 2009; Angelova, Regner, 2013; Bonroy et al., 2013; Mimra et al., 2016a,b). To solve the credence dilemma, institutions to protect consumers from being exploited might be a solution.

Dulleck et al. (2011) investigate how economic outcomes are affected by liability, verifiability and competition. They show that liability leads to a significant increase in trade volume and efficiency. By contrast, verifiability does not seem to have any significant influence which they ascribe to the coexistence of individuals' with heterogeneous distributional preferences. Another solution to solve the dilemma might be the implementation of price competition between experts. Huck et al. (2012) show experimentally that competition increases trust and market efficiency. Dulleck et al. (2011) conclude that competition drives down overall prices and increases the volume of trade which is confirmed by Mimra et al. (2016a). Additionally, they 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. To solve the credence dilemma second opinions or multiple visits of different experts are another approach. Wolinsky (1993) shows that the costs for visiting multiple experts determine whether this leads to an overall welfare increase. Mimra et al. (2016b) add to this by concluding that the rate of overtreatment significantly decreases with the possibility of second opinions and absolute market efficiency increases depending on additional search costs. In a more complicate theoretical model, Pesendorfer, Wolinsky (2003) show that the possibility for second opinions leads neither to Pareto optimal outcomes, as they are not incentive compatible, nor second best outcomes, since experts' effort levels remain too low, although this needs additional institutions like fixed prices.

The credence dilemma might also be solved by repuation building. Akerlof (1970) conjecture that brand-naming goods would lead to higher market efficiency as consumers curtail future expenditures if the quality does not fulfill their expectations. Darby, Karni (1973) support this assumption, suggesting that a good reputation allows experts to raise their prices without losing customers in future transactions. Furthermore,Wolinsky (1993) show that reputation can mitigate experts incentives to cheat. Roe, Sheldon (2007) confirm this for continuous or voluntary governmental labels that enable an outcome like under perfect information. However, corresponding experiments reveal ambiguous evidence. Dulleck et al. (2011) show that reputation increases trade volume and reduces overcharging, although this influence is driven to non-significance in markets with liability, verifiability or competition. Nevertheless, through reputation sellers are able to modestly increase their prices of high quality goods. In line with this, Mimra et al. (2016a) conclude that reputation and price competition have counteracting

effects, as experts with a bad reputation lower prices to compensate for it. By contrast, with fixed prices, consumers seem to take reputation much more into consideration. Grosskopf, Sarin (2010) confirm this by showing that additional information about experts past behavior with fixed prices leads to higher market efficiency. However, in comparing the concepts of private and public history, Mimra et al. (2016a) indicate that in markets with price competition the level of overcharging is significantly lower with revealed private history than with public history. They explain this counter-intuitive result, i.e. that more information about experts' past behavior lead to inferior market outcomes, by experts trying to compensate for declining prices due to fiercer price competition through higher overcharging rates.
The main problem in a market for expert services remains information asymmetry between experts and consumers. While formerly-mentioned mechanisms are primarily based on additional institutions, there might also be the possibility to solve the credence dilemma in reducing the information asymmetry. By introducing different states of knowledge for consumers, Darby, Karni (1973) show that experts' optimal level of fraud depends and decreases with better consumer knowledge. In line with this, Hadfield et al. (1998) and Howells (2005) argue that with additional information consumers can better protect themselves against bad deals while forcing experts to cooperate with their recommendations. This corresponds to the common-sense intuition that informed consumers are less likely to be exploited as they tend to accept fraudulent offers less often. However, Hyndman, Ozerturk (2011) conclude that experts' behavior depends on consumer information types rather than whether these are better informed. In line with this, Lee, Soberon-Ferrer (1997) as well as Fong (2005) argue that experts tend to cheat selectively based on consumers' identifiable characteristics. Bonroy et al. (2013) confirm this, as in a market with otherwise-homogeneous consumers who are committed to liable experts after diagnosis, they are less likely to invest in costly diagnosis the higher the risk aversion of consumers. In addition, Balafoutas et al. (2013) show that observable and audible characteristics of consumers, i.e. prosperity and country/city of origin, have a crucial influence on experts' fraudulent behavior.

Credence Goods Markets: The Influence of Additional Consumer Information

In "*Consumer Information in a Market for Expert Services: Experimental Evidence*", we investigate theoretically and experimentally the behavior in credence goods markets, in terms of how better-informed consumers might improve the outcome. In the literature, there is plenty of research about markets for expert services, although ex-ante consumer information has not gained much attention. However, providing additional consumer information is among the most prominent proposals to overcome the inefficiencies due to asymmetric information in credence goods markets. We investigate how consumers receiving an informative yet noisy signal before visiting an expert influences experts' cheating behavior, consumers' acceptance probabilities and overall welfare. In our theoretical model, we introduce three different treatments in which consumers receive either (1) an uninformative signal, (2) an informative signal observed by experts or (3) an informative signal hidden to experts.

We find that experts' likelihood of fraudulent behavior - i.e. recommending an expensive treatment when a cheap one would be sufficient to solve a consumer's problem - is influenced by ex-ante consumer information observed by experts. Our novel lab results thus confirm the findings of Lee, Soberon-Ferrer (1997), Fong (2005), Schneider (2012) as well as Balafoutas et al. (2013) drives that experts tend to cheat consumers conditional on their identifiable characteristics, which is given by the risk type in our setting determined by received signals. Our data shows that experts cheat high-risk consumers significantly more often than low-risk consumers, which supports the hypothesis by Hyndman, Ozerturk (2011) that hiding bad signals might be beneficial to consumers. Our results thus indicate that - in contrast to common sense - uninformed consumers are not the most likely victims of fraudulent behavior; rather, it is the informed high-risk type. In contrast to our theoretical predictions, we do not find any influence on experts' fraudulent behavior by hiding consumers' signals compared to the case of no ex-ante consumer information.

Moreover, our results show a significant influence of consumers' information on their acceptance probability - i.e. their likelihood of market entry - for expensive treatments. Without additional information, consumers show substantially lower rates of acceptance than suggested by theory. This might be due to consumers hoping for a minor problem, in which case the outside option doubles their income in comparison to accepting an expensive treatment. In the worst case, they fall back on the outside option and suffer from a serious problem, which only reduces their income by 20%. Accordingly, the risk in monetary terms of an untreated serious problem compared to a treated one is quite small. Based on this consideration, it is quite surprising that consumers substantially change their behavior and show very high acceptance probabilities when receiving bad signals. Since consumers condition their behavior on the signals received, more serious problems are treated appropriately with informative signals. However, there is no evidence that consumers account for experts' ability to observe their signals, as they behave similarly in terms of accepting probabilities in case of hidden and open signals.

Aggregate income increases when there is additional consumer information. This stems from consumers' tendency to reject expensive treatment recommendation if they do not distinctively receive a bad signal. In case of open signals, low cheating probabilities associated with good signals meet low acceptance rates of expensive treatments, whereas bad signals are associated with high cheating probabilities and high acceptance rates. This results in more realized contracts and more consumer problems are solved appropriately. In case of hidden signals, experts tend to cheat as if there was no consumer information, while consumers with bad signals show higher acceptance rates of expensive treatments. Again, there are more contracts realized and especially more serious problems solved.

In sum, markets for expert services generate superior levels of overall welfare when there is additional ex-ante consumer information. This is driven by experts benefiting from more frequently-accepted expensive treatment recommendations, implying more realized contracts and fewer outside option payments. Whether consumers benefit or not crucially depends on risk types, whereby low-risk consumers are better off and high-risk consumers are worse off when introducing additional consumer information.

Credence Goods Markets: The Effect of Qualifying Experts I

In "*Effects of Qualification in Expert Markets with Price Competition and Endogenous Verifiability*", we investigate theoretically how the introduction of heterogeneous experts regarding their ability to diagnose consumer problems affects the behavior and outcome in a market for credence goods. In such markets, consumers are neither able to observe effort decisions nor whether an expert is high or low skilled, which results in a moral hazard problem. We analyze expert and consumer behavior in a market where experts have a moral hazard problem in providing truthful diagnosis, since they have to invest in costly but unobservable diagnostic effort to send true signals to consumers. Rather than assuming a homogeneous level of qualification, in reality there are considerable differences in skills among experts in any given field. While Pesendorfer, Wolinsky (2003) assume that low-skilled experts always deliver an incorrect diagnosis, we argue that this depends on their willingness to invest effort in their diagnosis. Therefore, high-skilled experts' advantage only comprises being able to carry out diagnosis with less effort but not having monopoly power for correct diagnosis. For this reason, we introduce heterogeneous experts into the model of Pesendorfer, Wolinsky (2003), where consumers can visit multiple experts to verify recommendations. For simplification, we assume that experts are either high or low skilled. We model this by high-skilled experts having some probability of identifying consumer problems even with low effort, while low-skilled experts always give a false recommendation in this case.

Our results show that second best equilibria are possible in the presence of high skilled experts, even with flexible prices. However, such type of equilibrium being stable requires special market circumstances, whereby transaction costs for consumers must lie under a specific threshold. Additionally, the share of high-skilled experts needs to be relatively large and their edge in qualification relatively low. If these conditions are not fulfilled, it might be worthwhile for policy makers to intervene by fixing service prices to increase overall welfare. According to our results, there might be an incentive for policy makers to regulate service prices in markets with only few or rather extremely heterogeneously-qualified experts. However, if one drops the assumption that market composition cannot be influenced externally, there can be an incentive to regulate the share of high-skilled experts. Given that not only the possibility of second best equilibria but also any non-degenerate equilibrium depends on consumers' transactions costs not exceeding the determined threshold, market breakdowns might be prevented by reducing consumers' costs for visiting an expert. However, in any second best equilibrium, all welfare surplus is accumulated completely by either consumers or experts, which might make welfare maximization complicated in reality.

Credence Goods Markets: The Effect of Qualifying Experts II

In "*Expert Qualification in Markets for Expert Services: A Sisyphean Task?*", we build on our theoretical model from "*Effects of Qualification in Expert Markets with Price Competition and Endogenous Verifiability*" and test them in a laboratory experiment. We implement a classical 2*x*2 design by varying the share of high-skilled experts in the market and whether price competition exist. To our best knowledge, we are the first to provide an experimental design to investigate moral hazard in a market for credence goods. Besides looking at experts' high effort choices and consumers' search behavior, we investigate how markets react and use four indicators for efficiency, i.e. the volume of trade, the share of a maximum realized welfare, solved problems and the share of conducted wrong services.

We find that experts adapt their investment decisions to their individual skills but that 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 having their 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 behave risk averse. They seldom buy after a single diagnosis, frequently leave the market without any action and predominately opt for confirming diagnoses with other diagnoses before buying a service. While this causes higher transaction costs due to more visited experts and a welfare loss, 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 for 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 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 terms 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 overinvestments 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 but constantly declining prices over periods. 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 through the perceived higher degrees of freedom that experts experience by setting prices freely, thus increasing consumers' trust as they might interpret this as higher attachments to one's duties.

Summing up the second part of this book, it becomes evident that markets for credence goods are more complex than common economic games like the public goods game or the dictator game. With information asymmetries between consumers and experts, markets suffer from inefficiencies as consumers might be concerned about being cheated. Letting consumers be better informed before visiting an expert and qualifying experts regarding their necessary effort to provide correct diagnosis leads to more consumer trust and higher market efficiency. By contrast, hiding consumers' private information or introducing price competition in a market with many high-skilled experts do not appear to have positive effects on efficiency.

The present book adds to the broad field of investigations concerning what affects and determines human cooperation. It provides new insights into internal and external factors that influence such decisions. Rather than presenting a closed and universal examination, this book should be seen as an addition to an ongoing process. In particular, the theoretical model and the experimental design to investigate moral hazard in credence goods markets provide a useful basis for further research with strong potential for applicable policy and real-life implications.

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Chapter 2

THE VICTIM MATTERS: EXPERIMENTAL EVIDENCE ON LYING, MORAL COSTS AND MORAL BALANCING

with Kilian Bizer, Lukas Meub and Till Proeger

Author contribution:

Tim Schneider: 70 percent

Till Proeger: 10 percent

Lukas Meub: 10 percent

Kilian Bizer: 10 percent

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THE VICTIM MATTERS – EXPERIMENTAL EVIDENCE ON LYING, MORAL COSTS AND MORAL CLEANSING

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Abstract: In an experiment on moral cleansing with an endogenously manipulated moral self-image, we examine the role of the addressee of an immoral action. We find that cheating is highest and moral cleansing lowest when subjects cheat at the expense of the experimenter, while cheating is lowest and moral cleansing highest once cheating harms another participant. A subsequent measurement of subjects' moral self-image supports our interpretation that the occurrence of moral cleansing crucially depends on the moral costs resulting from immoral actions directed at individuals in different roles. Our results can help to explain the different propensity to cheat and conduct moral cleansing when immoral actions harm either another person or representatives of organizations.

Keywords: dictator game; laboratory experiments; lying; moral balancing; moral cleansing

JEL classification: C90 ; C91; D10

1. INTRODUCTION

Dishonesty and immoral behavior are constant features in human interaction and affect economic interactions. The propensity to act dishonestly is driven e.g. by personal characteristics and the situational context[1], but also the desire to maintain their moral self-image. Individuals derive utility from a favorable moral self-image, which is therefore kept at an individually optimal level (Bénabou and Tirole, 2011; Akerlof and Kranton 2000; Benjamin et al., 2010; Chen and Xin Li, 2009). Thus, the choice of engaging in immoral behavior exceeds the mere weighing of monetary costs and benefits and encompasses the individuals' current self-image, which is influenced by past and future actions. Previous actions that negatively affected the self-image lead to morally favorable actions (moral cleansing) – and vice versa (moral licensing) – to even out the imbalanced self-image (Battigalli et al., 2013; Merritt et al., 2010; Baumeister et al., 1994).

While previous experiments investigating moral balancing have relied on ex ante priming to induce a positive or negative self-image, Ploner and Regner (2013) have implemented an endogenous manipulation. A self-reported die roll enables lying to increase the individual payoff; in a subsequent dictator game, subjects can engage in moral cleansing by transferring money to another subject. However, while a substantial number of subjects cheated, little moral cleansing resulted. In this paper, we argue that the occurrence of moral cleansing crucially depends on the addressee of the preceding immoral action. It has been suggested that social concerns are activated to a different extent when cheating on individuals in different roles, such as fellow participants or the experimenter (Gneezy et al., 2013). We hypothesize that this notion extends to moral cleansing, whereby cheating on individuals in different roles incurs specific moral costs and a different inclination to balance the moral self-image. For an example of this argument, consider a street vendor falsely handing you too much change, compared to the taxman who falsely grants you the same amount of money at the cost of the state. While you have the opportunity to cheat an individual in both cases, your reactions may differ. We argue that the addressee of your decision determines the inclination to refrain from cheating and engage in subsequent moral cleansing. Consequently, the occurrence of moral cleansing could be explained by the decision context, particularly by the moral costs associated with cheating individuals in different roles.

2. EXPERIMENTAL DESIGN

To investigate the impact of different roles on cheating and subsequent moral cleansing, our experimental design builds on Ploner and Regner (2013). Similar to their setting, subjects' moral self-image is endogenously manipulated, by enabling them to cheat in a die roll that determines their endowment. Afterwards, they can donate to another player

[1] In the discussion on determinants of immoral behavior, different complementary explanations have been presented, e.g. regarding personal characteristics (Cappelen et al. 2013; Fosgaard et al., 2013; Gino et al., 2011; Gneezy, 2005; Pascual-Ezama et al, 2013; Shalvi and Leiser, 2013), situational circumstances as e.g. the anticipation of repercussions (Erat and Gneezy, 2012; Gneezy et al., 2013) or the individually ascribed importance of the individual moral identity (Gino et al., 2011).

in a standard dictator game as a means of moral cleansing. There is a benchmark treatment in which no cheating is possible (*control*), as well as two treatments in which cheating is conducted at the expense of either the experimenter (*cheat experimenter*) or another subject (*cheat partner*). The experiment comprises four parts.

In the first part, subjects claim their endowment by reporting the number of a role of a fair six-sided die. In *control*, the self-reported numbers are verified through the direct supervision of the experimenter, whereby no cheating is possible. In the other two treatments, die rolls are conducted in private. Reporting even numbers earns 15 ECU, and odd numbers 5 ECU. Reported numbers also determine the payoff for a matched partner, whereby it is randomly chosen whose die roll actually determines the endowments. Table 1 gives the payoffs related to the reported die rolls for all treatments. Note that the core difference between the treatments is at whose expense subjects can cheat. For *cheat experimenter*, the other subject will receive 5 ECU regardless, meaning that the additional payoff is taken from the experimenter. By contrast, in c*ontrol* and *cheat partner*, the individual decision to claim 15 ECU automatically reduces the other subject's payoff to 5 ECU.

reported die roll	own payoff	partner payoff
2,4,6	15 (15)	5 (5)
1,3,5	5 (5)	15 (5)

Table 1. Die roll and payoffs in ECU for *control* and *cheat partner* (*cheat experimenter*)

In the second part, after having reported the die roll, all subjects take the role of dictators in a standard dictator game and decide how much of their previously claimed endowment they want to donate to their partner.

In the third part, using a short, four-item questionnaire from Gino et al. (2013), we ask subjects for their current moral self-image, whereby they indicate their current feeling of *guilt*, *remorse*, *regret* and *overall self-image* (i.e. *how good of a person do you feel you are?)* on a Lickert scale from 1 to 7 (1= not at all, 7= to a great extent/very much).

Finally, participants are matched to pairs and randomly assigned the roles of dictators and recipients. Subsequently, the endowment claims and donation choices of the dictators are executed and displayed to both players.

For *control* / *cheat experimenter* / *cheat partner*, there were 4/3/3 sessions with 68/50/44 subjects. Experiments were conducted with a standard subject pool across disciplines in the Laboratory of Behavioral Economics at the University of Goettingen, using ORSEE (Greiner, 2004) and z-Tree (Fischbacher, 2007). Subjects were 24 years old on average, and 57% were female. The average session duration was 20 minutes whereby participants earned 6 € on average, including show-up fees.[2]

[2] Instructions and screenshots are available from the authors upon request.

3. RESULTS

3.1 Lying

A subject's endowment for the dictator game is determined by the reported role of the die. Figure 1 illustrates self-reported values and the resulting endowment claimed.

As expected, there is an equal share of high and low endowments claimed for *control* (exact binomial test, p=0.904). By contrast, subjects in *cheat experimenter* and *cheat partner* claim high endowments significantly more often (exact binomial tests, $p \leq 0.005$). Subjects are more willing to claim high endowments at the expense of the experimenter rather than the partner (Fisher's exact, p=.096).

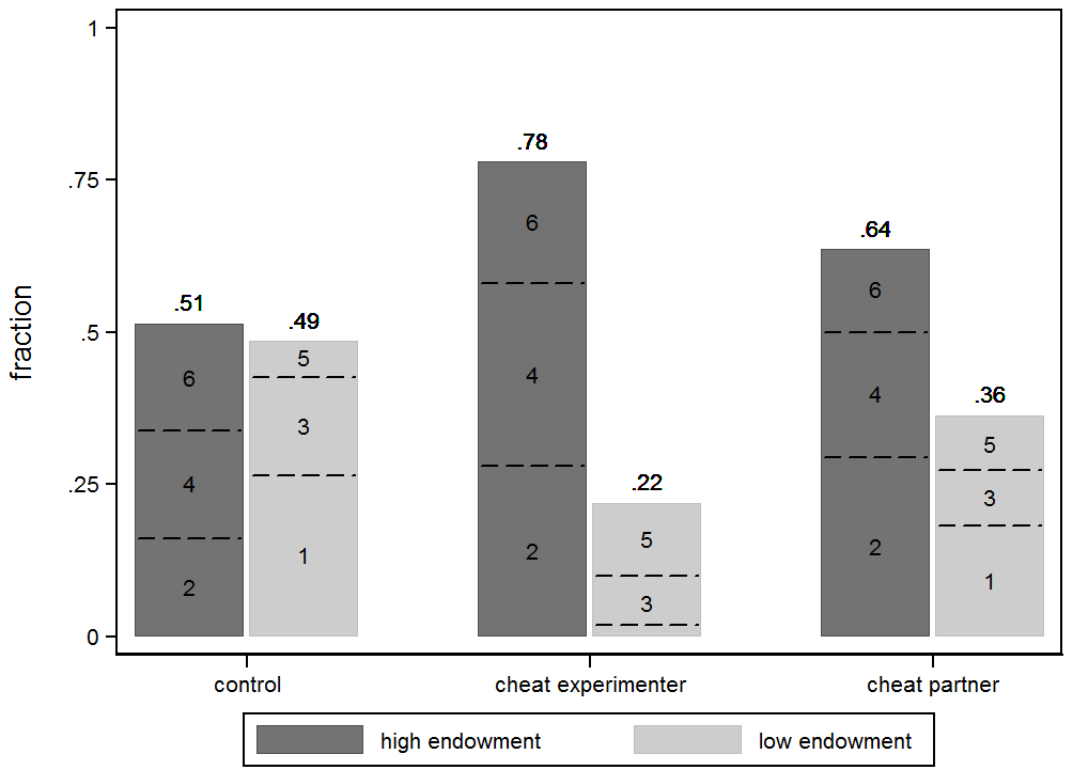

Figure 1. Claimed endowments by treatment

Note: The numbers in the bars represent the different die rolls.

To estimate the proportion of cheaters conditional on our treatment conditions, we apply the procedure introduced by Houser et al. (2012), giving us 56% of subjects reporting untruthfully in *cheat experimenter* and only 28% in *cheat partner*.[3]

Result 1: *Half of participants cheat on the experimenter, while only one quarter cheats on another participant.*

[3] Assuming that the population exclusively comprises strictly dishonest and honest people, the shares of cheaters can be estimated by assuming that the proportion of cheater equals $2p_h - 1$, whereby p_H is the share of high endowments claimed by subjects.

3.2 Giving

Figure 2 gives the distribution of donations of subjects who previously claimed a high endowment, i.e. those who potentially cheated, whereby the numbers in boxes indicate the respective averages.

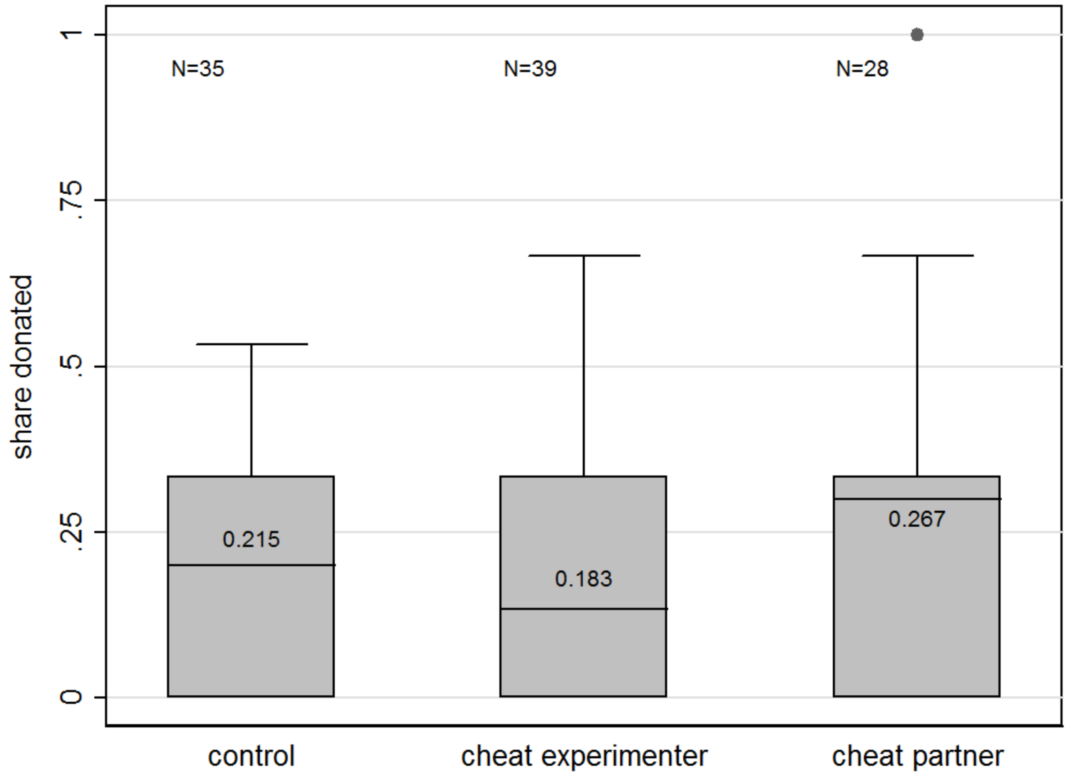

Figure 2. Giving in the dictator game by treatment

Overall, donations are in line with the typical results from dictator games (Camerer, 2003). Compared to *control*, subjects who (potentially) cheated on the experimenter tend to donate less; subjects donate more after cheating on another player. Note that the share of subjects donating nothing is roughly equal across treatments (.35/.34/.36). Recall that there are about twice as many dishonest reports of die rolls in *cheat experimenter*. Accordingly, differences do not stem from the higher share of subjects donating, but rather from the actual amount donated. In absolute ECU terms, subjects who chose to donate in *cheat partner* (mean=5.89, sd=3.26) give about 43% more than in *cheat experimenter* (mean=4.12, sd=2.18). Subjects in *cheat partner* donate significantly more than in *cheat experimenter* (WRS-test, z=-1.864, p=.0623). Furthermore, the predominant choice of cheating yet giving less in *cheat experimenter* does not support the assumption of a "Robin-Hood-Effect", i.e. cheating on the experimenter to give to other subjects.

Result 2: *Subjects who potentially cheated on the experimenter donate less than those who potentially cheated on another participant.*

3.3 Self-Image

Before seeing the game's final result, subjects report their feeling of *regret*, *guilt*, *remorse* and their *overall self-image*, as given in Figure 3 for subjects claiming a high endowment, i.e. those who potentially cheated.

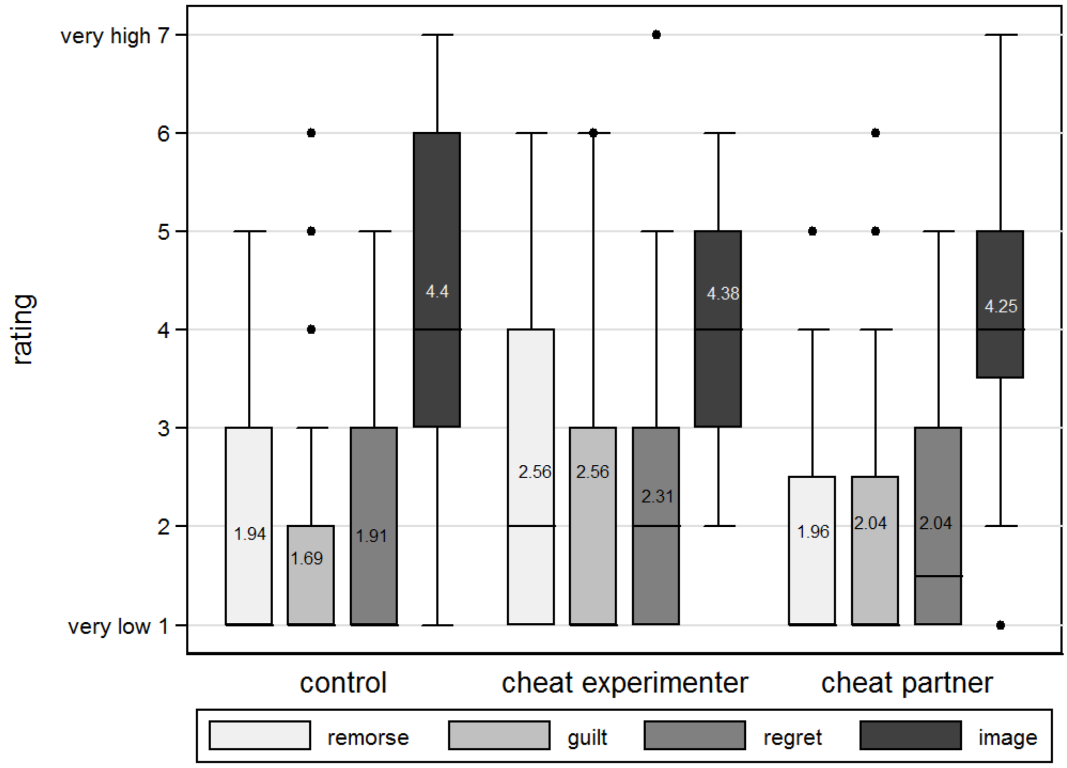

Figure 3. Self-image (high endowment) by treatment

The ratings are not substantially different across treatments, whereby the feelings of remorse/guilt/regret tend to be slightly stronger in *cheat experimenter*, where cheating is frequent and donations are small. This result can be interpreted such that cheating the experimenter incurs little moral costs, given that cheating subjects continue to hold a favorable self-image equal to subjects in *control* and thus do not require substantial donations in the dictator game as a means of moral cleansing. In *cheat partner*, fewer subjects decide to cheat in the first place, which does not affect their self-image negatively. The cheating subjects would then be the ones driving the higher donations in *cheat partner*, by compensating the moral costs of having cheated or the feeling that others may suspect them of cheating. Accordingly, as subjects either bypass or compensate moral costs, their self-image is not different from *control*.

Result 3: *The moral costs of cheating the experimenter are low; they are higher when cheating another participant. Consequently, cheating is avoided ex ante or compensated by moral cleansing ex post.*

4. CONCLUSION

We find that cheating the experimenter is widespread, incurring little moral costs and no reduction of the moral self-image; consequently, there is no substantial moral cleansing. Furthermore, no "Robin-Hood-Effect" occurs, as cheating the experimenter is not associated with substantial subsequent donations. By contrast, cheating at the expense of another participant halves the number of cheaters; obviously, a substantial share of subjects anticipates the moral costs and thus chooses not to cheat in the first place. Subjects who claim high endowments at the expense of another participant in turn donate significantly more, which can be interpreted as moral cleansing. Both reactions can be asserted through the moral self-image: as the moral costs of cheating another participant are dealt with by either avoiding them ex ante or cleansing them ex post, the moral self-image is equal to that of our control group.

More generally, it can be stated that once moral costs are high, e.g. when an opportunity to cheat on another person is taken, both avoiding the immoral action and moral cleansing occur. By contrast, frequent rational cheating and little ensuing moral cleansing will occur when the addressee is a faceless organization only evoking minor social concerns, as is conceivable e.g. for large corporations or the state. Picking up the example mentioned above, in most cases, one would point out the vendor's mistake to avoid the moral costs of cheating him. In fewer cases, one would proceed with taking the money, yet choose to do some good deed to ease one's bad conscience. Cheating the taxman would be considered morally acceptable to far more people and would not lead to the desire of sharing the profit. Our results thus emphasize the occurrence of moral balancing crucially depends on the addressee of immoral behavior. This could be crucial for the design of organizations characterized by a set of rules prone to cheating. Once individuals are given the opportunity to make profits by not adhering to (unenforced) rules, they will be more likely to engage in immoral behavior without feeling guilty when the victim is perceived to be an anonymous organization. Instead, if the organization credibly assigns the blame and punishment for losses incurred from cheating to a single person, rational cheating will be associated with substantially higher moral costs and will thus lead to the avoidance or – at least – compensation of immoral actions.

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Chapter 3

COOPERATION IN PUBLIC GOODS GAMES: ENHANCING EFFECTS OF GROUP IDENTITY AND COMPETITION

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Cooperation in public goods games: Enhancing effects of group identity and competition

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Abstract

A lot of economic and social situations can be described as contests in which agents need to distribute scare resources. Individual behavior plays an important role within these situations, while identity strongly impacts on behavior. This paper asks how group identity impacts the provision of a public good in a contest situation with different prize sharing rules. We show that group identity significantly increases contributions. Moreover, it turns out that identity affects how subjects react to different prize sharing rules. Our findings contribute to an increased understanding of the nature of group identity and its impact on economic behavior.

Keywords: group identity, contest, public goods game, multi-level interaction, experiment

JEL: C71; C92; D22; H41

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1 Introduction

In and outside economics exists a broad number of situations which can be described as contests in which agents need to use scarce resources like time, effort and money to affect the probability of winning a prize e.g. in political (win an election), economic (patents) and social environments (friends, university place) (Dechenaux et al., 2015). In this process individuals behavior plays an important role. But, beside a strong focus on contests in the theoretical literature, the empirical investigation of different contests is still limited (Dechenaux et al., 2015). On the other hand, identity strongly influences the behavior of individuals (Akerlof, Kranton, 2000, 2010). In line with this, recent research indicates that group identity increases the amount of how much weight is put on the welfare of other in-group members (Eckel, Grossman, 2005; Chen, Li, 2009). Identity gained increasing attention on the micro as well as on the macro level in the last years. Over the last decades countries are increasingly confronted with social as well as ethnic diversity (Jivraj, Simpson, 2015). Various facets of identity, for example discrimination tendencies have a huge impact on e.g. labor markets (Chen, Mengel, 2016). In contrast, on a micro level organizations are confronted with diverse teams, which might be a boosting factor for creativity and innovation, although diverse backgrounds might also be a stifling factor. Conflicts within and competition between groups are ubiquitous in everyday life (Chowdhury et al., 2016). Overall, a broad literature has emerged in recent years, studying the social roots, underlying cognitive aspects, as well as the economic outcomes of identity (Chen, Mengel, 2016).

To our best knowledge, it has not been investigated how identity affects contest situations. In the present paper, we explore experimentally how (artificial) group identity influences the willingness of individuals to cooperate in a standard public goods game extended by a contest situation (multi-level interaction). Our public goods game with the contest situation is based on Gunnthorsdottir, Rapoport (2006) and we complement it by introducing artificial group identity according to Eckel, Grossman (2005). We use partners matching, with the game lasting 10 periods. We employ four treatments (low and high identity with egalitarian and proportional profit sharing), each played 10 times, where we randomly assign subjects into two groups (à 4 persons). Within each group, individuals are engaged in a standard public goods game while competing for an exogenous and commonly known prize[3]. Groups increase their probability of winning the prize by investing more in their public goods. In the baseline experiment, the groups engage in the game, although no information about the group composition is revealed. In the high identity treatments, we use a puzzle task before the experiment starts and color tags to create artificial group identity in the lab. Moreover, we vary the monetary incentives of the contest (Gunnthorsdottir, Rapoport, 2006) by applying two prize-sharing mechanisms, either equally or proportionally according to individuals' contributions, among all members of the winning group. The rules are communicated before the individual decisions start.

[3] In reality, intra-group conflicts rarely appear as isolated incidences but are mostly accompanied by inter-group competition, i.e. a team or a company as in-group competes for an exogenous good with other teams or companies as out-groups (contest).

Our results indicate a significant and positive effect of increased group identity on individuals' willingness to cooperate in a public goods game in a competitive setting. The proportional profit sharing rule leads to higher investments in low identity treatments. [4] The results for the prize-sharing mechanism are reverse in the high identity treatment, there the highest level of cooperation can be observed under the egalitarian profit-sharing rule. Moreover, we find that the number of full cooperators is significantly higher in the high identity treatment.
The remainder of the paper is structured as follows. Section 2 gives a short overview of the literature background, section 3 introduces the theoretical framework, before section 4 describes the experimental design. Section 5 presents our results and the discussion and section 6 concludes.

2 Literature background

2.1 Determinants of contributions to a public good

Public goods games have a long tradition (e.g. Ledyard, 1995). Since the interests of sub-groups and individuals do not necessarily coincide, groups cannot be modeled as unitary actors. Individuals' behavior in groups is characterized simultaneously by cooperation and competition. They are confronted with contradictory incentives for either defecting to maximize their own payoff or cooperating to maximize the group's payoff. In economic standard theory individuals' contributions to public goods fall short of optimal amounts, since free-riding is the dominant strategy, especially in anonymous situations (Fischbacher et al., 2001). Players want to raise their monetary outcome with preferably low risk and low uncertainty (Fischbacher, Gächter, 2010; Fischbacher et al., 2001).
Various studies show that individuals in fact do not behave according to the standard model (Mullainathan, Thaler, 2000; Camerer, 2004; Chaudhuri, 2011), given that they do not regard their decision in isolation but rather take social motives into consideration. It is shown that contributions are influenced by various factors, such as group size (Isaac et al., 1994), marginal per capita return (MPCR) (Ashley et al., 2010; Zelmer, 2003), gender (for an overview, see e.g. Croson, Gneezy, 2009) or partners matching (Keser, Van Winden, 2000). Moreover, low levels of fear and greed also positively influence the willingness to cooperate (Ahn et al., 2001). Nonetheless, cooperation cannot be guaranteed, as most decisions are made under uncertainty and individuals' decisions and reactions are difficult to forecast. Cooperation is not based on confusion or errors (Keser, 1996), but rather on kindness - e.g. altruism or warm-glow (Andreoni, 1995) - strategic considerations such as conditional cooperation (Fischbacher et al., 2001), as well as by in-group attachment (Chen, Li, 2009), self-centered inequity aversion (Fehr, Schmidt, 1999), social preferences of positive reciprocity (Fehr, Fischbacher, 2002) or fairness preferences (Fehr, Schmidt, 1999; Bolton, Ockenfels, 2000). Further explanations for

[4] Our findings in the no-identity treatment are consistent with those of Gunnthorsdottir, Rapoport (2006), who show that the proportional prize-sharing rule outperforms the egalitarian one.

within-group cooperation are e.g. the minimal group paradigm (Chen, Chen, 2011; Li et al., 2011; Chen, Li, 2009; Tajfel et al., 1971) and common fate (Brewer, Kramer, 1986; Wiltermuth, Heath, 2009). Recent research analyzes also the role of identity (Eckel, Grossman, 2005).

2.2 Identity

Previous research indicates that identity[5], a person's sense of self (Akerlof, Kranton, 2000), has a strong impact on economic outcomes and affects individual behavior and decision-making (Chen, Li, 2009; Akerlof, Kranton, 2010), which makes it a relevant factor in the provision of public goods (Ashforth, Mael, 1989; Akerlof, 2002; Akerlof, Kranton, 2005; Ashforth et al., 2011). A broad literature has emerged in recent years, studying the social roots, underlying cognitive aspects, as well as the economic outcomes of identity (Chen, Mengel, 2016).

A positive effect of group identity on the level of cooperation is shown for single-level interactions (Solow, Kirkwood, 2002; Eckel, Grossman, 2005; Chen, Li, 2009). For example, Eckel, Grossman (2005) analyze how and whether identity mitigates shirking and free-riding behavior in a team production setting, showing that actions designed to enhance team identification significantly increase cooperative behavior. This is in line with early work. Already Gaertner et al. (1993) show that it is possible to create a common group identity through the simple manipulation of, prima facie, irrelevant variables, leading group members to perceive themselves in their group as a we, resulting in the elimination of negative factors rooted in in-group heterogeneity.

In recent years various studies analyzed identity showing that e.g. a "real identity" reduces free-riding (Chowdhury et al., 2016) and workers competition (Kato, Shu, 2016). Kato, Shu (2016) analyze the interplay of social identity and worker competition in a Chinese textile firm, with exogenously formed social groups and real productivity data in a real economic setting, providing empirical evidence that social identity has a significant impact on competition and affects the interaction of workers. Workers only compete against those with a different social identity but not against their in-group co-workers, while identity also influences the incentives promoting competition. Furthermore, holding different social identities reduces truth-telling (Rong et al., 2016) and identity-homogeneous groups are more likely to reveal less negative reciprocity in case of deviating behavior of group members (Bicskei et al., 2016), while a strong identity increases cooperation in the absence of punishment (Weng, Carlsson, 2015). Further studies e.g investigate discrimination, showing that this behavior varies depending on the type of identity (for a meta-analysis, see, e.g. Lane, 2016).

[5] The concept itself has a long tradition and its roots in psychology. Individuals' social identity is based on categorization (Tajfel, 1974; Turner, 1975; Tajfel, 1978, 1982), identification (in-group; out-group) (Stets, Burke, 2000; Tajfel, 1974) and comparison (Tajfel, 1974, 1978).

2.3 Contests and multi-level interactions in public goods games

A broad literature about contests emerged in the last decades (Konrad, 2009) but the number of articles investigating empirically individual behavior in different contest situations is still limited and only emerged within the last decade (Dechenaux et al., 2015). Some studies focus e.g. on group performance and communication in combination with egalitarian profit sharing (Sheremeta, Zhang, 2010; Cason et al., 2012), rent-seeking contests (Katz et al., 1990; Ahn et al., 2011) or the effects of proportional prize sharing (Kugler et al., 2010; Gunnthorsdottir, Rapoport, 2006).

Focusing on public goods games shows that recent experiments started to extend the literature about single-level interactions in public goods games by introducing multi-level interactions (contests). The interaction between several groups for winning an exogenous prize changes individuals' incentive structure, as free-riding might no longer be the dominant strategy. In a single-level dilemma, outperforming the others can be achieved by free-riding. But having a between-group conflict (contest situation) forces the rational self-interested individual to cooperate with her group members to win the conflict (Bornstein, Erev, 1994)[6]. Accordingly, the willingness to cooperate within a group also depends on the nature of the higher-level conflict (e.g. the contest as well as the incentive structure of the prize sharing mechanism). The findings of recent experiments indicate a positive effect of intergroup competition (Tan, Bolle, 2007; Burton-Chellew et al., 2010; Kugler et al., 2010) as well as pseudo-competition (Burton-Chellew, West, 2012) on the willingness to cooperate within groups. Intragroup conflicts embedded in an intergroup competition reduce free riding (Gunnthorsdottir, Rapoport, 2006).

3 Theoretical Framework

Following Gunnthorsdottir, Rapoport (2006), we introduce a market with n groups ($n \geq 2$) competing for an exogenous prize $S > 0$. Let m_k be the number of symmetric players in group k with $k = \{1,...,n\}$ and $m_k = \{2,...,K\}$. In sum, there are $\sum_{k=1}^{n} m_k = N$ symmetric players in the market. Each player i, with $i = \{1,...,N\}$, receives an endowment $e > 0$, which can be invested either in a public good or kept for oneself. We assume the strategy space to be continuous, implying that individual i, can contribute any share of her endowment e to the public good. We denote an individual's contribution to her group's public good by x_{ik} ($0 \leq x_{ik} \leq e$), the group's total contribution by X_k ($X_k = \sum_{i=1}^{m_k} x_{ik}$) and the overall contributions in the market of all N players by X ($X = \sum_{i=1}^{N} X_k$).

Given the usual within-group conflict in standard public goods games between investing or

[6] Between-group competition and within-group cooperation is also broadly discussed in social-psychology. Early work by (Sherif et al., 1961) indicates that an antagonistic relation between groups boost solidarity within groups. Overall, with positive dependencies between groups, i.e. a goal can only be reached jointly, cooperative forms of social interaction occur, while with negative dependencies between groups, i.e. the goal of one group can only be reached at the cost of the other group, competitive forms of social interaction occur.

keeping one's endowment, individuals' dominant strategy is to free-ride on other members, which reduces overall equilibrium contributions to zero. However, by introducing an exogenous prize, for which groups compete, individuals' incentive structure changes. This stems from the probability of winning being determined by group members' ability to cooperate, i.e. to generate a greater public good in comparison to other groups. Depending on prize value and how it will be distributed, it is no longer a dominant strategy to restrain from investing (Gunnthorsdottir, Rapoport, 2006).
Besides their pecuniary interests, individuals perceive themselves as parts of collectives i.e. groups rather than solely as independent entities. We argue that individuals decision-making for investing in public goods is crucially affected by their group identity, i.e. their attachment to groups. Accordingly, we will extend our framework by incorporating individuals' valuation for cooperation with in-group members into their payoff welfare function.

The within-group conflict
In accordance with the public goods literature (Zelmer, 2003; Ledyard, 1995), let x_{ik} be the share of endowment invested by player i of group k in the public good. The contributions from all members constitute a group's public good. The share of endowment not invested converts directly to an individual's payoff. Within each group, the investments in the public good are uniformly multiplied by the factor $t > 1$ and equally distributed among all members. We determine $g_k = te$ as the maximum payoff that each member can receive from the public good in group k, if all of its members invest their full endowment, i.e. if $X_k = m_k e$.
However, we define the actual payoff in group k from their public good by $g_k \frac{X_k}{m_k e} = \frac{tX_k}{m_k}$. This payoff equals zero, if everybody restrains from investing, i.e. $X_k = 0$. Since $t > 1$, members' full contribution would lead to the highest joint welfare. However, we exclude the trivial case when it would be a dominant strategy for individuals to invest their full endowment and thus we assume $t < m_k$. In sum, an individual's payoff from the within-group conflict is given by

$$\pi_{ik}^{in-group} = (e - x_{ik}) + \frac{tX_k}{m_k}. \tag{1}$$

The between-group conflict
Like Gunnthorsdottir, Rapoport (2006), we introduce an exogenous prize S for which all n groups compete. This extends the standard public goods game by between-group competition. The probability for a group of winning the prize, thereby, depends on the value of their own public good relative to the values of all other groups' public goods. By introducing a contest success function, groups can never be sure to win the prize even if their contribution outperforms all others'. This models real-life circumstances more appropriately, since there never appears to be certainty to succeed in competition, even if one's expenditures stand out (Gunnthorsdottir, Rapoport, 2006). Let the probability of group k winning the prize be given by

$$\Theta_k = \frac{X_k}{X}. \tag{2}$$

If group k wins the prize, it will be distributed among members according to the profit-sharing function f_k given by

$$f_k = \frac{x_{ik}^c}{\sum_{i=1}^{m_k} x_{ik}^c}, \tag{3}$$

with $0 \leq c \leq \infty$. Notice that parameter c determines the type of profit-sharing rule. For example, if $c = 0$, all members of the winning group k receive an equal share of the prize, $\frac{S}{m_k}$, which denotes a completely egalitarian profit-sharing. By contrast, if $c = 1$, each member of the winning group receives a share of the prize proportional to her individual investment to the public good, $\frac{x_{ik}}{X_k}$, which denotes a completely proportional profit-sharing. An individual's payoff from the between-group competition is given by

$$\pi_{ik}^{between-group} = \Theta_k S f_k = \left(\frac{X_k}{X}\right) S \left(\frac{x_{ik}^c}{\sum_{i=1}^{m_k} x_{ik}^c}\right). \tag{4}$$

Payoff structure

An individual's overall expected payoff depends on the outcome from both the within-group, as well as the between-group conflict. By combining equation (1) and (4), we derive the expected payoff for individual i as a member of group k, given by

$$\pi_{ik} = (e - x_{ik}) + \frac{tX_k}{m_k} + \left(\frac{X_k}{X}\right) S \left(\frac{x_{ik}^c}{\sum_{i=1}^{m_k} x_{ik}^c}\right). \tag{5}$$

Equilibria without group identity

In our set-up, individuals are confronted with diverging investment motives. On the one hand, they have an incentive to keep their endowment for themselves, since this has a higher expected payoff than investing in the public good, given the within-group conflict. On the other hand, investments increase their probability of winning the prize in the between-group conflict.

Lemma 1: *In the unique Nash-equilibrium with symmetric players without group identity, individuals invest* $x_{ik}^* = S\left(\frac{n-1+cn(m_k-1)}{[nm_k]^2(1-\frac{t}{m_k})}\right)$ *in their public good.*

Proof: To determine an individual's equilibrium behavior, we derive the first order condition of equation (5)

$$\frac{\partial \pi_{ik}^e}{\partial x_{ik}} = \frac{t}{m_k} - 1 + S\left(\frac{x_{ik}^c (X - X_k)}{X^2 \sum_{i=1}^{m_k} x_{ik}^c} + \frac{cX_k(x_{ik}^{c-1}(\sum_{i=1}^{m_k} x_{ik}^c) - x_{ik}^c(\sum_{i=1}^{m_k} x_{ik}^{c-1}))}{X \sum_{i=1}^{m_k} x_{ik}^{2c}}\right). \tag{6}$$

As we assume symmetric players, by rearranging and solving for x_{ik} we obtain[7]

$$x_{ik}^* = S\left(\frac{n-1+cn(m_k-1)}{[nm_k]^2(1-\frac{t}{m_k})}\right). \tag{7}$$

[7]For detailed calculations see Appendix C.

Remark: Due to symmetry in players, this strategy is the unique Nash-equilibrium. However, this strategy is not a dominant one and depends on individuals' expectations about other players' investment strategies. Moreover, we exclude the case in which the expected payoff from between-group conflict is excessively high, which would make it the dominant strategy for individuals to invest their full endowment, i.e. we assume

$$S \leq \frac{e(nm_k)^2(1-\frac{t}{m_k})}{n-1+cn(m_k-1)}. \tag{8}$$

As outlined by equation (7), individuals' equilibrium investments increase with the value of c, the multiplier t and the value of the prize S. In this equilibrium, each individual receives an expected payoff of

$$\pi^* = e + S\left[\left(\frac{n-1+cn(m_k-1)}{[nm_k]^2(1-\frac{t}{m_k})}\right)(t-1) + \frac{1}{nm_k}\right]. \tag{9}$$

All terms in the bracket are strictly positive, since $t > 1$ and $\frac{t}{m_k} < 1$. Individuals are better off by playing the equilibrium strategy x^*_{ik} rather than free-riding, as in classic public goods games. Consequently, introducing between-group competition moderates the within-group conflict and increases cooperation.

Equilibria with group identity

In the next step, we introduce group identity. This far, individuals have adjusted their behavior solely based on pecuniary incentives. However, individual decision making is influenced by a person's sense of self, more specifically by the degree of identification with one's membership in groups. Therefore, investment decisions can be expected to depend on in-group attachments, as high attachments will be accompanied by an urge for cooperation. In general, individuals try to maintain a comfortable self-image and deviations from ideal levels are associated with losses in utility (Akerlof, Kranton, 2005; Ploner, Regner, 2013). Linking it to our setting, we assume that individuals suffer from utility losses by less cooperative behavior towards favored group-members, respectively when they do not invest their full endowment, with the loss in utility increasing proportionally to the withheld amount.[8]

However, as described by Akerlof, Kranton (2005), as well as Huettel, Kranton (2012), such losses depend on the situational context. If individuals do not feel attached to their group, we cannot expect a loss in utility from non-cooperative behavior. To model this, we introduce z_{ik} ($0 \leq z_{ik}$) as the degree to which individual i from group k identifies with her group, namely the degree of her in-group attachment. An individual's expected utility function, formerly outlined

[8]We are aware that our assumption of full contribution as the social norm is quite strict. It might well be the case that a norm, denominated as w, is expected to be rather $x^*_{ik} \leq w \leq e$ instead of $w = e$. However, it can be expected that individuals will profit from a utility gain due to an overcontribution with $x_{ik} > w$, in the same way they will suffer from a utility loss by an underprovision with $x_{ik} < w$. Following this, assuming $x^*_{ik} \leq w \leq e$ instead of $w = e$ would not change the general argument of our analysis.

by equation (5), changes to

$$\pi_{ik}^{identity} = (1 - z_{ik})(e - x_{ik}) + \frac{tX_k}{m_k} + \left(\frac{X_k}{X}\right) S \left(\frac{x_{ik}^c}{\sum_{i=1}^{m_k} x_{ik}^c}\right). \tag{10}$$

The more that an individual identifies with her in-group, associated with higher values of z_{ik}, the greater her loss in utility by less cooperation. In contrast, individuals with a minimal group attachment, i.e. $z_{ik} = 0$, will base their investment decision purely on pecuniary aspects.

Lemma 2: *With group identity and symmetric players, an individual's optimal investment strategy depends on her intensity of in-group attachment z_{ik}:*

(1) *if $z_{ik} < 1 - \frac{t}{m_k}$, individuals invest $x_{ik1}^* = S\left(\frac{n-1+cn(m_k-1)}{[nm_k]^2(1-\frac{t}{m_k}-z_{ik})}\right)$,*

(2) *if $z_{ik} \geq 1 - \frac{t}{m_k}$, individuals invest their full endowment, $x_{ik2}^* = e$.*

Proof: In order to determine optimal behavior, we derive the first order condition of equation (10), given by

$$\frac{\partial \pi_{ik}^{iden}}{\partial x_{ik}} = z_{ik} - 1 + \frac{t}{m_k} + S\left(\frac{x_{ik}^c(X - X_k)}{X^2 \sum_{i=1}^{m_k} x_{ik}^c} + \frac{cX_k(x_{ik}^{c-1}(\sum_{i=1}^{m_k} x_{ik}^c) - x_{ik}^c(\sum_{i=1}^{m_k} x_{ik}^{c-1}))}{X \sum_{i=1}^{m_k} x_{ik}^{2c}}\right). \tag{11}$$

However, note that by introducing z_{ik}, incentives to invest in the public good have changed. Even while assuming that (8) still holds, it might become individuals' dominant strategy to invest their full endowment, depending on the actual value of z_{ik}. We need to distinguish two cases:

Case 1: $z_{ik} < 1 - \frac{t}{m_k}$
By determining the symmetric Nash equilibrium from equation (11), we derive individuals' optimal investment strategy

$$x_{ik_1}^* = S\left(\frac{n - 1 + cn(m_k - 1)}{[nm_k]^2(1 - \frac{t}{m_k} - z_{ik})}\right). \tag{12}$$

Case 2: $z_{ik} \geq 1 - \frac{t}{m_k}$
In this case, it is the strict dominant strategy for individuals to invest their full endowment. Since the expected payoff by deviating from full cooperation is negative, we derive

$$x_{ik_2}^* = e. \tag{13}$$

Remark: In both cases we observe strictly higher investments in public goods with increased group identity compared to the case of low identity, as long as $z_{ik} > 0$. Notice that the higher the number of in-group members m_k, the greater needs to be either an individual's in-group attachment z_{ik} or the multiplier t for public goods to attract her for full cooperation, which constitutes the circumstance of increasing difficulties to sustain stable cooperations with increasing group size.

Since stable cooperation leads to higher expected payoffs, overall welfare also increases. We conclude that the higher the group attachments in a setting with multi-level interactions, the more cooperative individuals are expected to become and the higher the investments in public goods.

4 Experimental design

Within their groups, subjects play a standard public goods game while simultaneously competing for an external and commonly-known prize (contest). The prize is distributed among members of the winning group by either the egalitarian, $c = 0$, or the proportional profit-sharing rule, $c = 1$, with the probability of winning depending on all players' contributions to their public good. Payoffs are denominated in tokens, accumulated over periods and paid at the end of the experiment, where one token corresponds to EUR 0.01.

In each session, eight subjects participate and are allocated randomly into two groups of four persons, i.e. $n = 2$ and $m = 4$. The allocation remains constant over all ten periods, $T = 10$[9]. For reasons of comparison of low and high identity treatments we need to play a partners matching[10]. At the beginning of each round, subjects decide how much of their endowment, $e = 50$, they want to invest in the public good. We set the maximum payoff from the public good to $g_k = 100$ to generate a marginal per capita return (MPCR) of 0.5.

The exogenous prize is determined by $S = 152$ (equal to Gunnthorsdottir, Rapoport, 2006) and awarded according to the contest success function (see (2)). Finally, after each round, subjects are informed about the prize-winning team, the underlying winning probabilities, their own payoff from the actual round, as well as how much they have earned over all periods played this far.

In *low identity* treatments, we allocate subjects randomly to either group 1 or group 2 without informing the subjects about the identity of their group members (minimal group identity).

By contrast, in *high identity* treatments group identity is artificially increased above the minimal group identity by using a puzzle task (according to Eckel, Grossman, 2005)[11]. In detail, subjects participate in an unpaid team-building task prior to the experiment, in which they jointly have to construct a puzzle. Moreover, we also use a special labeling of group red and group green rather than group 1 and 2, as well as equipping subjects with color tags to wear on their clothes

[9]The group size of four as well as 10 rounds is commonly in public goods experiments(Zelmer, 2003).

[10]Gunnthorsdottir, Rapoport (2006) use 80-round strangers matching. Previous research indicates that partners matching compared to strangers matching increases the level of contribution (Keser, Van Winden, 2000).

[11]Eckel, Grossman (2005) tested six different treatments to analyze the impact of team identity on team production, namely a baseline procedure, team color treatment, quiz treatment, puzzle treatment, wage treatment and tournament treatment. The puzzle task is the method of choice given that it leads to the highest level of contribution.

to present group affiliation. In the subsequent puzzle task, all subjects have to solve a colored puzzle, corresponding to their group color, in cooperation with their group members[12]. For this purpose, they are seated within their group, separated from the other group and are allowed to talk and support each other while solving the task. The groups had no information about the subsequent game to prohibit agreements or strategical planning.
The puzzle comprises five different pieces that add up to a square. However, since nobody possesses all five necessary pieces at the beginning, the subjects have to engage in trading with their group members. To enable comparison with *low identity* treatments, each subject there has to solve the same, but uncolored, puzzle task in separation and without knowing that they will play in groups in the subsequent experiment.
In all treatments, after the puzzle task was finished by each subject, the materials were collected, each of whom was placed alone in a cubicle and instructions for the subsequent task are distributed to the subjects. In addition, each cubicle was equipped with pen and paper for taking notes. After reading the instructions, all subjects had to pass a pre-experimental quiz to ensure their understanding of the instructions.
At the end of the experiment, the subjects had to complete a questionnaire. Besides general socioeconomic questions, we asked for individuals' in-group attachment. Subjects reported their degree of in-group attachment on a scale between 1 and 10, with higher scores representing stronger in-group attachment (Chen, Li, 2009)[13].

4.1 Treatment conditions

We employ four different experimental treatment conditions that differ in terms of group identity and prize-sharing mechanism.[14]

Low ID EG: Subjects solve the puzzle task in separation and are subsequently randomly allocated to group 1 or group 2. The prize is distributed equally among the winning team's members, i.e. $c = 0$.

Low ID PR: Subjects solve the puzzle task in separation and are subsequently randomly allocated to group 1 or group 2. The prize is distributed proportionally among the winning team's members, i.e. $c = 1$.

High ID EG: Subjects are allocated to group green or group red and solve the puzzle task in cooperation with their team members. Communication is possible during the puzzle task. The prize is distributed equally among the winning team's members, i.e. $c = 0$.

[12]For detailed instructions, see Appendix.
[13]On a scale from 1 (=absolutely not) to 10 (=extremely), how strong was your in-group attachment?
[14]Abbreviations are to read as follows: Low identity is abbreviated as *Low ID* and high identity as *High ID*. If the prize is shared equally the index is *EG* and in case of proportional profit sharing it is *PR*.

***High ID PR*:** Subjects are allocated to group green or group red and solve the puzzle task in cooperation with their team members. Communication is possible during the puzzle task. The prize is distributed proportionally among the winning team's members, i.e. $c = 1$.

Table 1 briefly summarizes the game parameters and Nash equilibria for all four treatments.

Table 1: Experimental conditions and game parameter

	Group size	No of Sessions	Endowment	Size of Public Good g_k	Rounds	Prize	High Identity	Nash Equilibrium
Low ID EG	4	10	50	100	10	152	0	4.75
Low ID PR	4	10	50	100	10	152	0	33.25
High ID EG	4	10	50	100	10	152	1	> 4.75
High ID PR	4	10	50	100	10	152	1	> 33.25

Note: High identity is coded as a dummy: 0 = artificial group identity is **not** increased, 1 = artificial group identity **is** increased.

4.2 Hypotheses

In order to predict subjects' cooperative behavior we insert our experimental parameters to our theoretical framework. By taking individuals' group identity into consideration, we expect higher investments in public goods with increased identity, meaning higher values of z_{ik}. According to the literature as well as the theoretical framework, individuals' behavior in social dilemmas is not purely driven by self-interest, with people being rather altruistic and conditional cooperators when they are part of a group and perceive themselves as a part of it. We assume that these effects will increase when group identity is made more salient, thus by intergroup competition and communication. We expect higher rates of cooperation in high identity treatments.

***Hypothesis 1*:** Investments in public goods are higher with increased group identity.

As outlined by the theoretical framework, individuals adjust their investment behavior according to the prize-sharing mechanism, with a higher investment leading to a higher value of c. We expect subjects to invest more in public goods under the proportional sharing rule, $c = 1$, than under the egalitarian sharing-rule, $c = 0$.

***Hypothesis 2*:** Investments in public goods are higher under the proportional than under the egalitarian profit sharing rule.

Based on the theory, if z_{ik} exceeds the value of $1 - \frac{t}{m_k}$, full cooperation becomes the dominant strategy. By increasing group identity, more individuals are expected to become full cooperators, defined as individuals who invest their entire endowment, $e = 50$ tokens, in each round.

***Hypothesis 3*:** The number of full cooperators increases with increased group identity.

4.3 Experimental procedure

The experiment was conducted between May and July 2016 in the Laboratory for Behavioral Economics at the University of Goettingen. The experiment was programmed using zTree (Fischbacher, 2007). Participants were recruited with ORSEE (Greiner, 2004). We implemented a 2 x 2 design, crossing the dimensions IdentitynoIdentity and egalitarian profit sharingproportional profit sharing. Before the start of the main task, subjects went through a puzzle task either alone (no identity) or as a team (identity). 320 subjects participated in 40 sessions, which lasted about 45 minutes, with average earnings of EUR 11.17. Approximately 53% of the participants were female[15]. Overall participants were 24 years old[16] and roughly 41% of the participants are economics or business administration students[17].

5 Results and discussion

In the following section, we investigate how subjects willingness to cooperate is affected by (I) their group identity and (II) the applied profit-sharing rule. Furthermore (III), we analyze the interplay of identity and full cooperation. We start by reporting the data overview and summary statistics, followed by non-parametric and parametric tests. The main interest behind our experiment is the individual behavior, which cannot be depicted by averages. Given the panel structure of the data (320 individuals played in groups of eight over 10 rounds in 40 sessions), the main part of the analysis will be the regression analysis. A simple way of regression is just to control for clustered standard errors. A superior way is to treat the data set as a panel data set, which *"explicitly recognizes that n subjects are observed making a decision in each of T time periods"* (Moffatt, 2015, p. 90). Accordingly, for a more detailed view of how contributions are affected by identity and profit-sharing rules, we apply tobit panel models including the typical control variables.

5.1 Analyzing the effects of low vs. high identity

First, we study the effects of increased group identity on the level of contribution, comparing low and high identity treatments. We find significant differences between the mean contribution. On average, individuals mean contributions in low identity treatments are $\bar{x}_{\text{Low ID}} = 40.55$ tokens in contrast to $\bar{x}_{\text{High ID}} = 43.51$ tokens in high identity treatments (see Table 2). Overall,

[15]Participants played in mixed groups. We find no differences for gender.

[16]We find no effect of age on the level of contribution. When interpreting such age effects we need to keep in mind that they might be due to different social conditions of the cohorts in other studies.

[17]Economic students are assumed to behave more rational. We find that economic students, ceteris paribus, contribute less than students from other fields. But, this effect is driven by the behavior in the low identity sub-sample. Here, economics students cooperate significantly less than those from other disciplines, while this effect is not observable in the high identity treatment. This indicates that the social incentive is stronger than the monetary incentive and that it outweighs a fully rational behavior.

differences between low and high identity treatments on group level are significant at a 5% level (Mann-Whitney-U[18]: $z = -2.056, p = 0.0398$).

Table 2: Summary statistics

	Low ID	**Low ID EG**	**Low ID PR**	**High ID**	**High ID EG**	**High ID PR**
Mean contribution	40.55	39.27	41.83	43.51	44.38	42.64
SD	10.77	10.57	10.88	9.83	9.73	9.91
25%-quantile	35	32.8	39.7	41.2	43.25	40.6
50%-quantile	44.75	40.75	46.85	48	49.85	45.5
N	160	80	80	160	80	80

Note: Table 1 displays statistics of individuals decisions, therefore*N* denotes the number of individuals participated in each treatment.

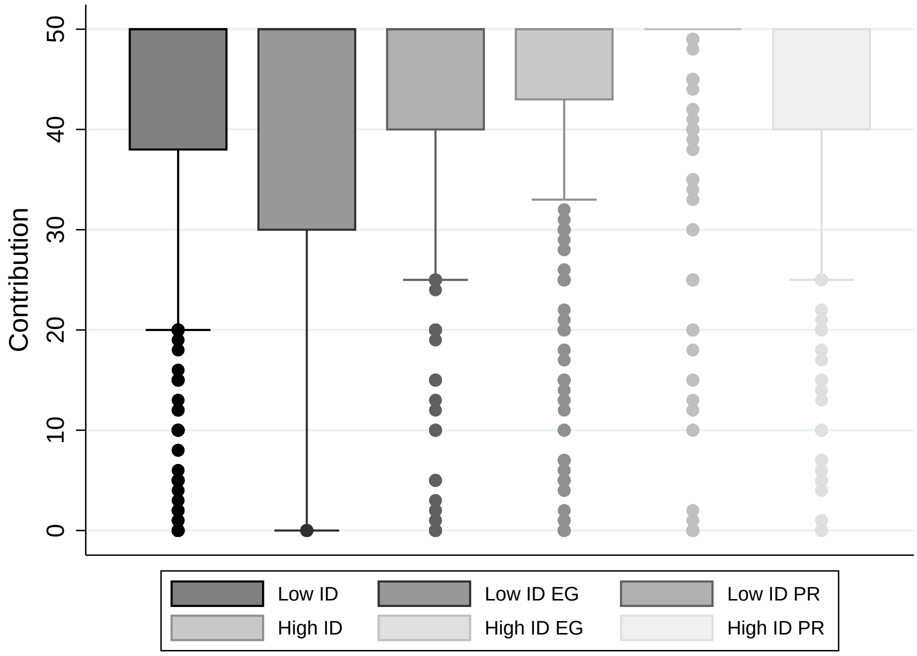
These findings are in line with previous research indicating that identity (Chen, Li, 2009; Eckel, Grossman, 2005) as well as between-group competition (Gunnthorsdottir, Rapoport, 2006) positively influences the level of contribution. Our results show that even the pure introduction of competition leads to significantly higher contributions (one-sample t-test: $t_{\text{Low ID EG}}(79) = 29.205, p_{\text{Low ID EG}} = 0.0000$ and $t_{\text{Low ID PR}}(79) = 7.058, p_{\text{Low ID PR}} = 0.0000$) than the predicted Nash equilibrium[19] (see Table 3).

The boxplot (Figure 1) displays distributional details for low and high identity treatments in general, with both differentiated as well by profit-sharing rules.
Additionally, we plot investments over all ten rounds to analyze whether the observed pattern is driven by individual behavior in one or particular rounds.

The positive effect of high group identity can be found for all ten rounds (see Table 2). Overall and in each single round, investments are higher in the high identity treatment. Contributions in low as well as high identity treatments increase from round one ($\bar{x}_{\text{Low ID}} = 37.98, \bar{x}_{\text{High ID}} = 41.86$) to two ($\bar{x}_{\text{Low ID}} = 42.19, \bar{x}_{\text{High ID}} = 44.29$). A paired t-test reveals that the difference is significant at the 1%level ($t_{\text{Low ID}}(159) = -4.332, p_{\text{Low ID}} = 0.0000$ and $t_{\text{High ID}}(159) = -3.364, p_{\text{High ID}} = 0.0005$) (See Appendix for details.)[20].
In sum, variations of investments are lower under the high identity treatments. This indicates that identity can sustain cooperation and increase the level of contribution. Contrary to previous findings of public goods games, we find that contributions are almost stable over time in the high identity treatment. Our results suggest that free-riding-reducing incentives, namely increased group identity and competition for monetary rewards, shift the focus from pure selfish interests to welfare maximizing considerations. Subjects only sometimes contribute 0 and the number of these actions on group level is significantly higher in the low identity treatment compared with the high identity treatment (Mann-Whitney-U: $z = -11.662, p = 0.0000$).

[18]We use independent observations (group level) for the Mann-Whitney-U test.
[19]Mean values are tested against the Nash equilibrium of 4.75 for LOW ID EG and 33.25 for LOW ID PR.
[20]Furthermore, in both treatments we observe a significant end-game effect from round nine to ten (paired t-test: $t_{\text{Low ID}}(159) = 2.101, p_{\text{Low ID}} = 0.0186$ and $t_{\text{High ID}}(159) = 2.976, p_{\text{High ID}} = 0.0017$).

Figure 1: Contributions to the public goods game - low and high identity



However, we find no individual full free-riding (≙ contribution of 0) over all ten rounds.

Our results are similar to the findings of Eckel, Grossman (2005), indicating that increased group identity leads to increasing contributions from the first round to the second and relatively stable contributions until the end-game effect kicks in.

We only have ten independent observations per treatment given our data structure (group-level), whereby the power of the non-parametric tests is limited. For a more nuanced view of how contributions are affected by identity, it is helpful to simultaneously control for several variables such as profit-sharing rule, age, gender and pre-experimental experience while using tobit panel models[21], treating our dataset as a panel data set. Table 3 displays the results of these estimations. Accordingly, we estimate different models: first, we introduce step-wise the main interesting variables (whole data set). The analysis of sub-samples offers a more detailed insight into the data, thus secondly, we estimate three models for each subsample (low and high identity), while step-wise including the main interesting and control variables.

[21] We use these censored regression models given our data structure. Our dependent variable is the level of contribution. It is a non-negative integer and it is in the range from 0 to 50.

Table 3: Regression results

	Full model						Sub-sample: low identity			Sub-sample: high identity		
	(1a)	**(1b)**	**(1c)**	**(1d)**	**(1e)**	**(1f)**	**(2a)**	**(2b)**	**(2c)**	**(3a)**	**(3b)**	**(3c)**
High Identity	13.417***		13.5***	4.553	1.850	−0.162						
	(3.537)		(3.54)	(4.861)	(4.551)	(3.775)						
Egalitarian PSR		2.261	2.596	−6.205	−7.867	−4.684	−7.067	−8.593**	−5.109	11.681**	9.166*	8.141**
		(3.561)	(3.491)	(4.813)	(4.494)	(3.748)	(4.489)	(4.265)	(3.566)	(5.400)	(4.942)	(4.133)
*High Identity * Egalitarian PSR*				18.257**	17.920**	13.403*						
				(6.982)	(6.523)	(5.479)						
Attachment					3.681***	2.620***		2.984***	2.025***		4.590***	3.394***
					(0.580)	(0.495)		(0.738)	(0.627)		(0.904)	(0.770)
Investment own group in t-1						0.367***			0.374***			0.362***
						(0.028)			(0.036)			(0.044)
Prize won in t-1						9.691***			8.713***			12.096***
						(2.333)			(3.065)			(3.687)
Profit in t-1						−0.345***			−0.319***			−0.409***
						(0.056)			(0.071)			(0.093)
Female	−4.466	−4.991	−4.55	−3.687	−3.362	−3.089	−0.297	0.716	0.097	−7.847	−8.435*	−6.802
	(3.516)	(3.590)	(3.519)	(3.499)	(3.267)	(2.726)	(4.552)	(4.309)	(3.584)	(5.479)	(5.006)	(4.163)
Economics	−7.919*	−6.962	−7.841**	−8.589*	−9.202**	−7.695**	−11.489**	−12.308***	−10.345***	−5.778	−6.110	−4.785
	(3.566)	(3.632)	(3.569)	(3.547)	(3.318)	(2.771)	(4.604)	(4.363)	(3.637)	(5.412)	(4.951)	(4.105)
Experimental experience	1.304*	1.075*	1.323**	1.264*	1.21*	0.762	1.226*	1.129*	0.792	1.476*	1.495**	0.878
	(0.522)	(0.529)	(0.523)	(0.519)	(0.485)	(0.405)	(0.688)	(0.652)	(0.546)	(0.791)	(0.724)	(0.601)
Age	−0.391	−0.235	−0.419	−0.436	−0.401	−0.344	−0.646	−0.398	−0.319	−0.133	−0.347	−0.295
	(0.562)	(0.572)	(0.563)	(0.557)	(0.521)	(0.434)	(0.780)	(0.739)	(0.613)	(0.799)	(0.731)	(0.606)
Constant	65.566***	68.426***	64.833***	69.762***	49.733***	27.9*	74.687***	53.272***	26.494*	66.976***	44.685**	28.659*
	(13.060)	(13.324)	(13.1)	(13.099)	(12.619)	(11.302)	(17.907)	(17.659)	(15.716)	(18.804)	(17.746)	(15.960)
Obs	3200	3200	3200	3200	3200	2880	1600	1600	1440	1600	1600	1440
σ_u	28.346***	29.046***	28.35***	28.014***	25.848***	20.605***	25.588***	23.975***	18.930***	30.354***	27.232***	21.583***
	(1.657)	(1.697)	(1.657)	(1.638)	(1.528)	(1.423)	(2.015)	(1.914)	(1.829)	(2.666)	(2.415)	(2.182)
σ_e	21.274***	21.272***	21.275***	21.275***	21.235***	20.350***	22.178***	22.137***	21.318***	20.070***	20.033***	19.068***
	(0.542)	(0.542)	(0.542)	(0.542)	(0.540)	(0.559)	(0.750)	(0.748)	(0.779)	(0.779)	(0.777)	(0.796)
ρ	0.64	0.651	0.64	0.634	0.597	0.506	0.571	0.540	0.441	0.696	0.649	0.562
AIC	11583.26	11597.18	11584.71	11579.91	11542.81	9854.368	6609.1	6595.235	5609.86	4972.839	4949.933	4251.518
BIC	11631.82	11645.75	11639.35	11640.62	11609.59	9937.886	6652.122	6643.635	5673.129	5015.861	4998.333	4314.786

Tobit panel model with 0 for lower limit and 50 for upper limit. Estimations for whole sample (1a-f) and sub-samples(2a-c and 3a-c).Dependent Variable: Level of contribution to group's own public good. Standard errors in parentheses: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

When taking a closer look at the regression table (see Table 3), the positive impact of increased group identity on cooperative behavior is confirmed, whereby the coefficient is positive and highly significant. Going a step further, we interact high identity with the egalitarian profit sharing rule. Model 1d-1f indicate that the effect is mainly driven by the profit sharing rule. Egalitarian profit sharing is a mechanism which treats all individuals in the same way. Separating the data into two subsamples indicates that the egalitarian profit sharing rule has a negative impact in the low identity treatment while its impact in the high identity treatment is positive. Our results indicate that artificially increased group identity in the laboratory triggers cooperative behavior, with the strongest effect under the egalitarian profit sharing rule. It seems that increasing group identity leads individuals to feel that he or she should put more weight on the welfare of other in-group members.[22]

These results are mirrored when focusing more narrowly on the perceived level of group attachment. This step is made because group identity is associated with group attachment (Chen, Li, 2009), which is a basis for social identity. We asked the participants to value the strength of their in-group attachment. The coefficient of the group attachment variable is positive and highly significant in all models, while the effect is higher for high identity treatments. This indicates that higher perceived in-group attachment triggers higher contributions. Our results are in line with the findings of Chen, Li (2009), showing a positive effect of in-group attachment.

Result 1: Contributions to public goods are significantly higher with increased group identity.

5.2 Prize sharing mechanism

Differentiating the low identity condition by profit-sharing rules (Table 2), we find a lower mean value on group level with $\bar{x}_{\text{Low ID EG}} = 39.27$ for egalitarian profit-sharing compared to the proportional profit-sharing with $\bar{x}_{\text{Low ID PR}} = 41.83$ (Mann-Whitney-U: $z = 1.209, p = 0.2265$). The MWU Test is thus insignificant and indicates no difference between the profit-sharing rules in the low identity treatment[23]. Comparing our results to the expected equilibrium contributions (see Table 1) shows that in contrast to our assumptions, under both profit-sharing rules higher average contributions are realized in the low identity treatments. Possible explanations for these high contributions, compared to the usual values in public goods games, are that we use a partners matching and that we introduce a contest. Even without any artificial increased group identity, the group competes for an exogenous prize against another group. Partners matching

[22] This is in line with findings of e.g. Chen, Li (2009); Solow, Kirkwood (2002); Kagel, Roth (2016). Already Gaertner et al. (1993) showed that it is possible to induce group identity by manipulating seemingly irrelevant variables. The puzzle task is a team-building task which leads to higher cooperative behavior, as previously shown by Eckel, Grossman (2005).

[23] If cooperative behavior is rewarded, cooperation is a rational strategy. The results of Gunnthorsdottir, Rapoport (2006) indicate that proportional rewarding looms larger than equal rewarding, which can be explained by the non-satiation axiom of choice theory. Thus, our results are in contrast to their findings, indicating only small differences between the profit sharing rules.

as well as contests are mechanisms which lead to an increase of cooperative behavior (Keser, Van Winden, 2000).

Figure 2: Investments - low identity per round

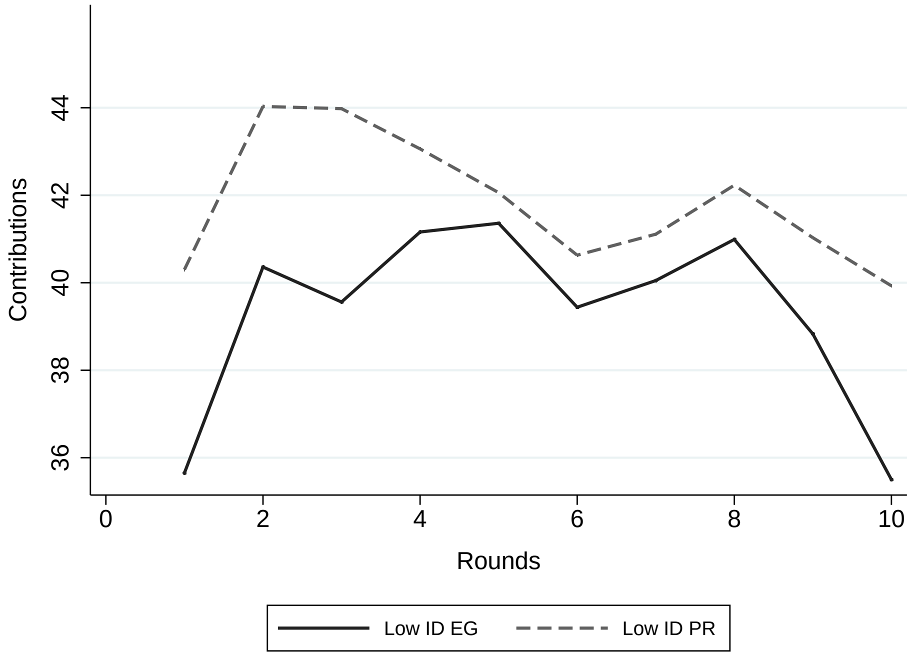
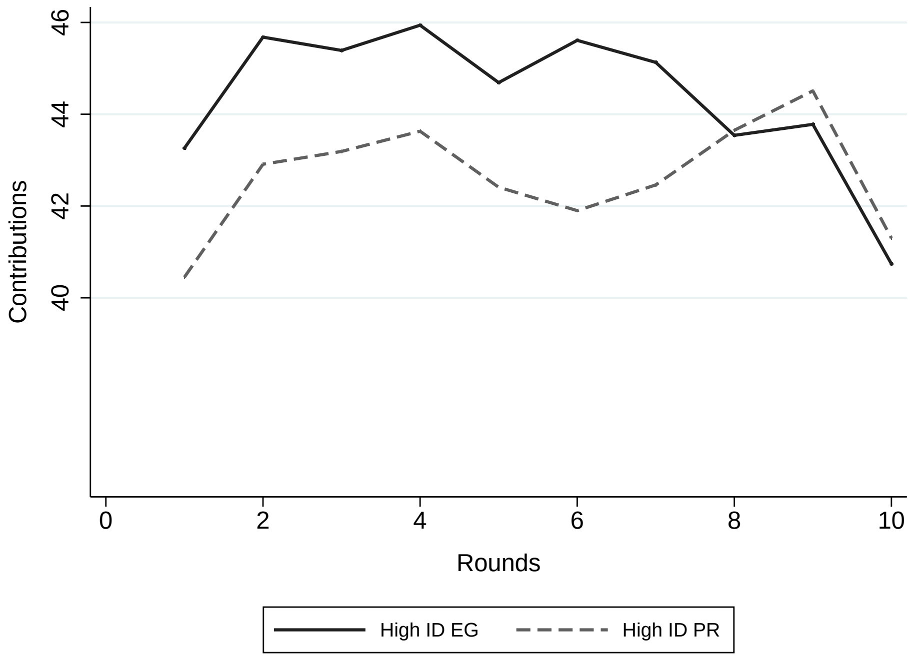


Figure 3: Investments - high identity per round



In high identity treatments, the mean contributions for both profit-sharing rules contradict hypothesis 3 as they show an opposite pattern in comparison to low identity treatments (Table 2). The contribution under the egalitarian profit-sharing rule on group level shows a higher mean value with $\bar{x}_{\text{High ID EG}} = 44.38$ tokens, compared to proportional profit sharing with a mean value of $\bar{x}_{\text{High ID PR}} = 42.64$ tokens (Mann-Whitney-U: $z = -1.436, p = 0.1509$). The MWU test is insignificant and indicates no difference between the profit-sharing rules in the high identity treatment. Nevertheless, the contribution is slightly higher under the egalitarian profit sharing rule. This particular result is in contrast to the findings of Gunnthorsdottir, Rapoport (2006), and a first, careful interpretation might be that identity is the reason for the reverse effect of the profit sharing rules in the high identity treatment.

Given the limited number of independent observations, the power of our non-parametric tests is limited. Taking a closer look at our regression results (Table 3), we find support for our hypotheses that both profit-sharing rules impact on the level of contribution, albeit in different ways. Overall, there is no effect of the profit-sharing rule (1a-1f). Dividing the sample into the two sub-samples confirms what was already observable in the tendencies of the descriptive (non-significant) results. While we find no effect in the main (full) model (1f), this might be due to the circumstances that they offset each other. Analyzing the subsamples indicates that the egalitarian profit sharing rule has a strong negative effect in the low identity treatment (2a-2c), while the effect is positive and significant in the high identity treatment (3a-3c). This indicates that the social incentive is stronger than the monetary incentive[24], which could be an explanation for higher mean contributions in the high identity treatment with equal prize sharing. Our findings for the low identity treatment, that proportional sharing is favored, are in line with those of Gunnthorsdottir, Rapoport (2006).

Result 2: Egalitarian and proportional profit sharing differ in their impact on individuals willingness to contribute. Contributions are higher under the proportional profit sharing rule in low identity treatments. Increasing identity leads to a reverse result. In high identity treatments contributions are higher under the egalitarian profit-sharing rule.

These findings are surprising upon first glance. As outlined by the theoretical framework and the complemented basic experiment (Gunnthorsdottir, Rapoport, 2006), we expected investments in public goods to be higher under the proportional rather than the egalitarian profit-sharing rule, given their different monetary incentives (Kugler et al., 2010).

There might be a plausible explanation for these findings. The egalitarian profit-sharing rule can be described as a more *social* sharing rule, given that all group members profit equally from a prize won. By contrast, the proportional profit-sharing rule is more related

[24] Additionally, having a closer look at the low identity treatment shows that the number of fully non-cooperative decisions per round (contribution$\hat{=}$ 0) in the low identity treatment is significantly higher under the equal profit sharing (6.5%) compared to the proportional (4.125%) profit-sharing rule (Mann-Whitney-U: $z = 9.165, p = 0.0000$ and see, Appendix Table 4). Analyzing this for the high identity treatment shows that the number of fully non-cooperative decisions per round (contribution$\hat{=}$ 0) in the high identity treatment is again significantly higher under the equal profit sharing (4.5%) compared to proportional (2%) profit sharing rule (Mann-Whitney-U: $z = 7.141, p = 0.0000$ and see, Appendix Table 4).

to rational economic behavior, since in this case individuals receive a higher expected payoff from investing in public goods, which should lead to higher equilibria contributions. While in low identity treatments these monetary incentives could outweigh social considerations, in high identity treatments individuals are primed to pro-social behavior due to the preceding team-building task, thus they might be more receptive for the influence of egalitarian sharing, which reverses the possible effects of the profit-sharing rules. Our results indicate that identity has a positive impact on the contribution level. Therefore, it might not be so surprising that subjects behave in a more social manner in the high identity treatments. Explanations in line with this argumentation are e.g. in-group attachment (Chen, Li, 2009), fairness preferences (Fehr, Gächter, 2000) and social preferences (Fischbacher, Gächter, 2010). Chen, Li (2009) show that individuals' distribution preferences are affected by their degree of group attachment, with subjects being more generous and less envious towards their in-group members. Moreover, group attachment changes reciprocal behavior as good intentions are more often positively rewarded and misbehavior less often rewarded towards in-group matches in comparison to out-group matches. Our group-attachment variable (Table 3) is positive and highly significant, giving support to this assumption. In addition, Fischbacher, Gächter (2010) show that social preferences can sustain cooperation. Nevertheless, contributions decline because people in general are imperfect conditional cooperators. Fehr, Schmidt (1999) argue that fairness can also be interpreted as self-centered inequity aversion. According to their model, we could assume that sharing the prize equally among group members reduces inequity, while a proportionally shared prize enhances inequity; even though cooperative behavior is more rewarded under the proportional prize sharing mechanism. Furthermore, we could assume that increased group identity, especially the way we increased it, i.e. meeting group members in person and successfully conducting a group task, ascribes more importance towards inequity aversion among group members.

5.3 Group identity and full cooperation

As derived by theory, if z_{ik} exceeds or equals the critical value of $1 - \frac{t}{m_k}$, full cooperation becomes the dominant strategy. Overall, 100 out of 320 individuals are full cooperators, with 36 full cooperators in low identity treatments and 64 in high identity treatments. In absolute terms, the number of full cooperators is significantly higher (Mann-Whitney-U: $z = -9.950, p = 0.0000$) with increased group identity.

Result 3: The number of full cooperators is significantly higher in high identity treatment.

6 Summary and concluding remarks

We explored experimentally how increased group identity impacts individuals' willingness to cooperate in a contest setting in the present paper. For this purpose, we played a public goods game with two groups competing for an exogenous price and introduced artificial group identity by using a puzzle task. We used a standard 2x2 design with partners matching by varying the level of group identity as well as added a contest with an exogenous and commonly-known prize (either egalitarian or proportional).

Our results show that first, investments in public goods increase with increased group identity and subjects' willingness to cooperate increases through artificially increased group identity in a contest setting. Secondly, we had thought that investments in public goods are higher under the proportional than under the egalitarian profit sharing rule. This can be confirmed for the low identity treatments. Subjects invest less in public goods under the egalitarian sharing rule than under the proportional one. The effect is reverse in high identity treatments as subjects contribute significantly more to the public good under the egalitarian profit-sharing rule. This finding is astonishing as it contradicts previous findings indicating a stronger effect of the proportional profit sharing rule. Possible explanations for this finding could be e.g. inequity aversion (Fehr, Schmidt, 1999). The third point we assumed was that the number of full cooperators increases with increased group identity. Looking at the varying prize-sharing mechanisms shows that the number of subjects who fully cooperate is significantly higher when group identity is artificially increased.

Our findings contribute to a better understanding of group behavior and the role of identity in a contest setting. Summing up all results shows that cooperative behavior can be described by, at least, three factors: first, increasing group identity and perceived in-group attachment impact positively and significantly on the willingness to cooperate; second, contest situations (e.g. external monetary incentives, even if they are not certain) increase cooperation. And third, history, or to be more precise, the previous rounds, matter, especially if group members experience a positive event within their group, like winning the prize or the high investment of group members.

Appendix A: Tables

Table 4: Free-riding per treatment and round

	Rounds										
	1	2	3	4	5	6	7	8	9	10	Total
Low ID EG	3	4	4	4	4	6	3	3	8	13	52 out of 80
Low ID PR	0	0	1	1	4	5	4	3	7	8	33 out of 80
High ID EG	2	1	2	2	4	3	3	5	5	9	36 out of 80
High ID PR	0	0	1	0	3	4	2	1	0	5	16 out of 80
Total	5	5	8	7	15	18	12	12	20	35	137 out of 320

Table 5: Mean individual contribution per round and treatment

	Low ID		**Low ID EG**		**Low ID PR**		**High ID**		**High ID EG**		**High ID PR**	
Round	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	37.98	14.57	35.65	15.91	40.3	12.78	41.86	13.14	43.28	12.36	40.45	13.81
2	42.19	12.62	40.36	14.50	44.03	10.17	44.29	11.1	45.68	9.92	42.91	12.06
3	41.77	13.2	39.56	14.98	43.98	10.8	44.29	11.51	45.39	11.34	43.19	11.65
4	42.09	13.17	41.13	14.12	43.06	12.15	44.78	10.24	45.94	10.05	43.63	10.35
5	41.71	14.26	41.36	14.45	42.06	14.15	43.55	13.25	44.69	12.59	42.41	13.87
6	40.03	16.08	39.44	16.1	40.63	16.14	43.76	12.92	45.61	11.6	41.9	13.95
7	40.58	14.37	40.05	14.23	41.11	14.58	43.79	13.03	45.13	12.05	42.46	13.89
8	41.61	14.4	40.99	14.27	42.23	14.59	43.59	13.32	43.54	14.82	43.65	11.72
9	39.93	17.31	38.83	17.12	41.02	17.53	44.14	12.44	43.78	14.2	44.51	10.47
10	37.61	18.58	35.3	19.54	39.92	17.38	41.02	16.12	40.74	16.82	41.3	15.48
Mean	40.55	10.77	39.27	10.57	41.83	10.88	43.51	9.83	44.38	9.73	42.64	9.91
N	160		80		80		160		80		80	

Appendix B - Instructions

Puzzle instructions (Task 1)
All instructions were originally written in German and are available upon request. The puzzling instructions for low identity treatments were included in zTree and participants received envelopes containing the puzzle while being seated at computers. The puzzling instructions for high identity treatments were printed and laid out on tables where all members of a group were seated to solve the task together. The participants did not receive any information about what kind of treatment they played.

Instructions for the first task (in low identity treatments)
Your task in the $1st$ part is to form a **square**.
The following rules must be obeyed during the course of this exercise:

1. Open the envelope and take out the pieces of the puzzle.
2. You have 5 different pieces; each piece exists only once.
3. You have to puzzle until you solve it.
4. The puzzles have a gray top side and a white bottom side. The gray side must always face upwards.
5. When you have solved the puzzle, please click the "next" button and wait for further instructions.

Instructions for the first task (in high identity treatments)
The task of your team in the $1st$ part is to form five squares of equal size. The task will not be complete until each team member has before him/her a perfect square of the same size as that held by all other team members.
The following rules must be obeyed during the course of this exercise:

1. Open the envelope and take out the pieces of the puzzle.
2. In the beginning, each of you has 5 different pieces.
3. You have to exchange and puzzle together with your group members until each of you has solved his/her puzzle.
4. The puzzles have a colored top side and a white bottom side. The colored side must always face upwards.
5. There are 5 different pieces and each piece exists 4 times. Each player needs one piece of each kind to solve his/her puzzle.
6. You may not simply throw pieces into the center for others to take; you must give the piece directly to one other team member. Team members may give pieces to other team members but may not take pieces from other team members.
7. When all group members have completed their puzzle, you are allowed to talk about whatever you want. Please remain seated and wait for further instructions. You do not need to give any signal to the adviser.

Experimental Instructions (Task 2)

Depending on the treatment, subjects received different instructions: T1: low identity treatment, T2: high identity treatment; a: egalitarian profit-sharing rule, b: proportional profit-sharing rule.

Instructions for the second task

You are about to participate in an experiment in which two groups (á 4 players) play for winning a lottery (in each round). 10 rounds will be played with an identical course. [T1: At the beginning, you will be allocated randomly to either group 1 or group 2] [T2: You play in group red/green]. Within the experiment, there are two types of interaction:

1. *The within-group interaction* and
2. *The between-group interaction*.

Both types of interaction are compensated. Therefore, your final payoff depends on your decisions, your group members' decisions and the decisions of the other group's members.

<u>The course for each round in brief:</u>

1. Each player receives an endowment of **50 tokens**.
2. Each player decides how many tokens of his/her endowment he/she wants to provide for his/her group's project. It is possible to provide any integer amount between 0 and 50 tokens. These tokens of the endowment that are not provided will be kept for oneself.
3. The tokens provided by all players of a group generate the **group project**. Each of the two groups generate an independent group project. The number of tokens provided to one's group project are **doubled** and **distributed equally** among all group members.
4. Both groups play to win a lottery. The probability of winning the lottery depends on the total sizes of the group projects of both groups. The **larger** one's own group project **the more likely** it is to win the prize.
5. At the end of each round, you will receive a summary of the results.

<u>General information</u>

- All decisions during the experiment are anonymous. You will not receive any information on the individual decisions of the other players at any point of time.
- Earned tokens will be rounded to the nearest integer number.
- At the end of the game, tokens earned will be converted into euros and paid out (1 token = EUR 0.01).

(1) Within-group interaction

In every round, a group project is generated based on the group members provided tokens. The sum of tokens provided by all group members equals the value of this group's project. **At the end of every round, the value of the group project is multiplied by 2 and distributed equally among all 4 group**

members. Tokens not provided to the group project move directly into one's payoff.

For each player, the payoff from the *the within-group interaction* is, consequently, based on the retained tokens (first square bracket) and the payoff from the group project (second square bracket).

$$\text{Payoff from the } \textit{the within-group interaction} = $$
$$[\text{Endowment of 50 tokens} - \text{Tokens provided for group project}] + [\frac{\text{Value group project} * 2}{4 \;\; \text{players}}]$$

Examples

- If all group members retain their entire endowment for themselves, each member receives a payout of 50 tokens in this round from *the within-group interaction* (50 tokens from the private account; 0 tokens from the group project) $\rightarrow \frac{4*0 \text{ tokens } *2}{4 \; players} = 0$ tokens $/player$.
- If all group members provide their entire endowment to the group project, each member will receive a payout of 100 tokens in this round from *the within-group interaction* (0 tokens from the private account; 100 tokens from the group project) $\rightarrow \frac{4*50 \text{ tokens } *2}{4 \; players} = 100$ tokens$/player$.

(2) Between-group interaction (lottery)
In every round, your group plays against the other group to win a lottery. It is only possible for either your group or the other group to win. The payoff amounts to 152 tokens. The winning group is determined by the probability displayed below. This implies that no group can be certain to win the prize, even if it has a higher probability of winning than the other group. However, the probability of one group winning can be influenced by the number of tokens provided to the group project. **The larger one's own group project compared to the other group's project, the higher the probability of one's own group winning the lottery in this round**.

$$\text{Probability of your group winning the lottery} = $$
$$\frac{\text{Value your group's project}}{\text{Value of your group's project + Value of the other group's project}}$$

Example
Assume that group 1 provides 100 tokens to their group project and group 2 provides 200 tokens to their group project, then...
- the probability of group 1 winning the prize is $\frac{100}{100+200} = 33\%$;
- the probability of group 2 winning the prize is $\frac{200}{100+200} = 66\%$.

Distribution of the lottery payoff (in case your group has won)
If your group has won the prize, the payoff of 152 tokens is distributed [T1a,T2a: equally among all members of your group. In this case, each member of your group receives

$$38 \text{ tokens } \left(= \frac{152}{4}\right)]$$

[T1b, T2b: proportionally among all your group's members according to individuals' provisions to the group project. Therefore, your share of the lottery payoff depends on the number of tokens that you provided to the group project, as well as the number of tokens provided to the group project by your group members]

Example:
Player 1 provides 40 tokens to the group project. His/her group members provide 20 tokens each. Consequently, the group project has a value of 100 tokens. Assume, that this group wins the lottery, then the lottery payoff is distributed as follows: player 1 receives a share of 61 tokens from the lottery prize (152 tokens $*\left(\frac{40}{100}\right) = 60,8 =$ **61 tokens**) and her group members receive 30 tokens each (152 tokens $*\left(\frac{20}{100}\right) = 30,4 =$ **30 tokens**).]

In case your group does not win the lottery, you will receive any payoff from *the between-group interaction*.

Information about total payoff per round
In each round, your total payoff comprises the payoff from *the within-group interaction* as well as of the payoff from *the between-group interaction* (lottery).

Appendix C: Derivations

For simplification, we use $\sum_{i=1}^{m_k} x_{ik}^c = \sum x_{ik}^c$.

$$\begin{aligned}
\frac{\delta \pi_{ik}^e}{\delta x_{ik}} &= \frac{t}{m_k} - 1 + S\left(\frac{x_{ik}^c(X - X_k)}{X^2 \sum x_{ik}^c} + \frac{cX_k(x_{ik}^{c-1}(\sum x_{ik}^c) - x_{ik}^c(\sum x_{ik}^{c-1}))}{X \sum x_{ik}^{2c}}\right) \\
&= \frac{t}{m_k} - 1 + S\left(\frac{x_{ik}(X - X_k}{X^2 \sum x_{ik}^c} + \frac{cX_k(x_{ik}^{c-1}(\sum x_{ik}^c) - x_{ik}^c(\sum x_{ik}^{c-1}))}{X \sum x_{ik}^{2c}}\right) \\
&= \frac{t}{m_k} - 1 + S\left(\frac{x_{ik}^c(\sum x_{ik}^c)(X - X_k) + cXX_k(x_{ik}^{c-1}(\sum x_{ik}^c) - x_{ik}^c(\sum x_{ik}^{c-1}))}{X^2 \sum x_{ik}^{2c}}\right).
\end{aligned}$$

Assuming symmetric players gives $x_{ik} = x_i$, $X_k = m_k x_i$, and $X = nm_k x_i$ and changes the former equation to

$$\begin{aligned}
&= \frac{t}{m_k} - 1 + Sx_i^c\left(\frac{m_k x_i^c[(n-1)m_k x_i] + cn(m_k x_i)^2(x_i^{-1} m_k x_i^c - x_i^{c-1})}{(nm_k x_i)^2[m_k]^2 x_i^{2c}}\right) \\
&= \frac{t}{m_k} - 1 + Sx_i^c\left(\frac{[m_k]^2 x_i^{c+1}(n-1) + cn(m_k x_i)^2 x_i^{c-1}(m_k - 1)}{[nm_k]^2[m_k]^2 x_i^{2+2c}}\right) \\
&= \frac{t}{m_k} - 1 + S\left(\frac{n - 1 + cn(m_k - 1)}{[nm_k]^2 x_i}\right).
\end{aligned}$$

Finally, solving for x_i gives

$$x_{ik}^* = S\left(\frac{n - 1 + cn(m_k - 1)}{[nm_k]^2(1 - \frac{t}{m_k})}\right).$$

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Chapter 4

CONSUMER INFORMATION IN A MARKET FOR EXPERT SERVICES: EXPERIMENTAL EVIDENCE

with Kilian Bizer and Lukas Meub

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Consumer Information in a Market for Expert Services: Experimental Evidence

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Abstract

Markets for expert services are characterized by information asymmetries between experts and consumers. We analyze the effects of consumer information, where consumers suffer from either a minor or serious problem and only experts can infer the appropriate treatment. Consumer information is a noisy signal that is informative about a consumer's problem severity. In a laboratory experiment, we show that consumers are generally reluctant to accept expensive treatment recommendations, which is endorsed by good signals and fundamentally changed by bad signals. Experts condition their cheating on a consumer's risk of suffering from a serious problem if they can observe consumer information. Accordingly, experts and low-risk consumers benefit at the expense of more frequently cheated high-risk consumers. Consumer information leads to more appropriate treatments being carried out and thus superior overall welfare. In contrast to our theoretical predictions, this effect does not depend on hiding consumer information for experts.

Keywords: consumer information; credence goods; experts; laboratory experiment

JEL: C70; C91; D82

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1 Introduction

In markets for expert services, consumers are incapable of determining adequate treatments or services to solve their problem of a certain severity. Experts can perfectly infer both a problem's severity and the adequate service to solve the problem. Due to this ex ante information asymmetry, consumers have to purchase not only an expert's service but also information given by the expert's superior knowledge. In addition, ex post information asymmetries are immanent as consumers are unable to verify the received service's quality. Consequently, experts have incentives to exploit their superior knowledge trough overcharging, undertreatment or overtreatment (Dulleck and Kerschbamer 2006, 2009; Dulleck et al. 2011). Consumers anticipate this exploitation and might thus refrain from contracting with experts. This leads to market inefficiency or even market breakdown (Akerlof 1970). Examples of markets for expert services are plentiful, with physicians, car mechanics, taxi drivers, home improvement contractors and lawyers - to name just a few - providing services that match the outlined framework.

To protect consumers from being exploited while enhancing market efficiency, politics and consumer groups have made consumer information campaigns their principle. This principle is rooted in the idea that by equipping consumers with additional information, they are better protected against bad deals while forcing experts to be more sincere in their recommendations (Hadfield et al. 1998; Howells 2005). This approach has undoubtedly grown in importance and tremendously expanded in scope over the last couple of years, complemented by the development of various official websites, online initiatives aggregating and making available user content (information) such as Wikipedia or communication through social media or message boards. Consumers gather information about their likely problems and adequate services at minimal cost, even for very specific issues (Murray 1991). However, the theoretical analysis by Hyndman and Ozerturk (2011) challenges the folk wisdom assuming the general desirability of providing more consumer information since experts might exploit this information to customize their fraudulent service offers trough consumer discrimination. Our paper accounts for this development and growing importance of consumer information and researches into this field by considering both consumer entry decision and expert cheating behavior.

Despite numerous studies on the effects of consumer knowledge about experts' past behavior, e.g. Akerlof (1970), Darby and Karni (1973) and Dulleck et al. (2011), those on the effects of varying consumer information sets remain scarce. To our best knowledge, we are first in introducing a controlled laboratory study on the influence of varying consumer information on a market for expert services. Nonetheless, our model builds on the work by Hyndman and Ozerturk (2011) and Fong (2005), who show that this varying information and experts' ability to observe it are crucial in assessing the likely outcomes on markets for expert services. Further, our analysis connects well to field studies in markets for expert services like Balafoutas et al. (2013) and Schneider (2012). Our paper thus adds to theoretical and empirical findings. The key advantages of the laboratory approach lies in the possibility to shed light on consumer decision-making. In field studies, one might learn about expert cheating behavior but nothing much can be learned about consumer behavior as only consumers actually treated by experts are observed. However, whether consumers with a certain set of information tend to enter the market or not has to be considered crucial to the efficiency of markets featuring expert services and thus in the design of policy instruments.

Our experimental design thus evaluates the effects of additional consumer information that alters the distinct properties of the information asymmetry between consumers and experts. Consumers have either a serious or minor problem that needs to be solved by an expert service. Before visiting an expert, consumers receive a noisy signal about their problem severity. Liable experts observe the actual problem severity and recommend a verifiable cheap or expensive treatment, whereby the cheap treatment only solves a minor problem and the expensive treatment solves both. Accordingly, the only possibility for experts to cheat is given by overtreatment.[1] Consumers either accept the treatment recommendation, resulting in the corresponding payoffs, or reject the treatment leaving the expert and consumer with an outside option payment. This gives the consumer entry decision. Following a random matching protocol to avoid reputation building, we introduce three treatments: (1) consumers receive an uninformative signal, (2) consumers receive an informative signal observed by experts and (3) consumers receive an informative signal hidden to experts. Our (3) treatment builds upon the finding of Hyndman and Ozerturk (2011) who show that it might be optimal for consumers to hide their information to avoid being cheated according to specific cheating tolerances.

While fraudulent behavior is evident across all treatment conditions, our results confirm the findings of Lee and Soberon-Ferrer (1997), Fong (2005), Balafoutas et al. (2013) as well as Schneider (2012), who show that experts tend to cheat consumers conditional on their identifiable characteristics, i.e. they cheat high-risk consumers more frequently than neutral ones and low-risk consumers the least. In contrast to our theoretical predictions, experts' fraudulent behavior remains unaffected from hiding consumer information. Consumers' acceptance rates - i.e. their likelihood of entering the market - of expensive treatments are quite low in the absence of consumer information, substantially increase with bad signals and drop with good signals. Overall, more contracts are realized given additional consumer information, whereby more problems are solved and aggregate welfare increases. However, superior aggregate welfare benefits experts through more realized contracts and low-risk consumers by being cheated less, while high-risk consumers are cheated more frequently and become worse off.

[1] Liability precludes experts from undertreating consumers, while verifiability precludes overcharging.

Our findings add to the research on markets for expert services, whereby we deal with credence goods. The term credence goods was introduced in the seminal paper by Darby and Karni (1973), where "*generally speaking, credence goods have the characteristic that though consumers can observe the utility they derive from the good ex post, they cannot judge whether the type or quality they have received is the ex-ante needed one*" (Dulleck et al. 2011, p.526). In the subsequent strand of literature, it is generally assumed that consumers hold only vague information about their problem that needs to be addressed by an expert (Angelova and Regner 2013; Emons 2001; Pesendorfer and Wolinsky 2003; Roe and Sheldon 2007). Homogeneous consumers are only aware that they suffer from either a minor or a serious problem with common probabilities (Bonroy et al. 2013; Dulleck and Kerschbamer 2006, 2009; Dulleck et al. 2011; Mimra et al. 2013, 2014; Wolinsky 1993).

Despite numerous investigations about varying mechanisms to overcome market inefficiencies in expert markets,[2] research about solving the dilemma through additional consumer information is sparse. Darby and Karni (1973) show that experts' optimal level of fraud is likely to decrease with consumers' knowledge. This corresponds to the folk wisdom that informed consumers are less likely to be exploited as they more commonly tend to decline experts' faulty advice. However, Hyndman and Ozerturk (2011) show that in comparison to a setting with uninformed consumers, experts' cheating behavior depends on the specific signals: experts cheat consumers with a minor problem most often when they have received a bad signal, whereas consumers receiving a good signal are cheated the least. The authors conclude that more information does not necessarily lead to less fraudulent expert behavior. In addition, Lee and Soberon-Ferrer (1997) as well as Fong (2005) confirm that experts tend to cheat selectively based upon consumers' identifiable characteristics. Bonroy et al. (2013) show that in a market with homogeneous consumers who are committed to a liable expert once she gives a recommendation, the higher the consumers' risk aversion, the less likely experts are to invest in costly diagnosis. Fong (2005) - in accordance with Pitchek and Schotter (1987) and Hyndman and Ozerturk (2011) - conclude that consumers could be better off by withholding specific information, i.e. their expectation about having a rather serious problem and being likely to require expensive treatment. Balafoutas et al. (2013) identify consumers' observable characteristics - e.g. income or city of origin - as being decisive for experts' tendency towards fraudulent behavior. In their field experiment, taxi drivers in Athens were significantly more likely to overtreat and overcharge non-locals and high-income customers when compared to locals and low-income customers. The authors conclude that these differences in observable characteristics determine an expert's perception of a consumer's information set. This perception translates to differences in a fraudulent act's expected profit

[2] The effect of reputation and/or brand-naming goods (Akerlof 1970; Darby and Karni 1973; Grosskopf and Sarin 2010; Dulleck et al. 2011; Mimra et al. 2013); the influence of competition (Dulleck et al. 2011; Mimra et al. 2013); the possibility for second-opinion (Wolinsky 1993; Mimra et al. 2014).

and ultimately in different probabilities for consumers to be cheated. Overall, the effects of enhanced consumer information depend on the distinct signals received and the experts' ability to observe these signals. Additional information does not imply superior market outcomes per se in the context of expert services.

The remainder of this paper is structured as follows. Section two presents our theoretical framework, before section three describes our experimental design and section four states our hypothesis. Section five presents our results and finally section six concludes.

2 Theoretical Framework

Following the notation by Hyndman and Ozerturk (2011), we model a market for expert services. Consumers suffer from either a minor or serious problem, denoted by $\omega \in \{m, s\}$. While they cannot observe their problem severity, the probability of suffering from a serious problem is common knowledge and given by $Pr(\omega = s) = \alpha \in (0, 1)$. Each consumer visits one (*monopolistic*) expert, who can perfectly infer a consumer's problem and recommends either a cheap treatment at fixed price p_m and cost c_m or an expensive treatment at p_s and c_s, where $p_s > p_m$ and $c_s > c_m$. An expensive treatment solves both problem types, whereas a cheap treatment solves only a minor problem. If a consumer accepts the recommendation, the corresponding expert has to carry out the recommended treatment, i.e. treatments are assumed to be *verifiable*. Given that we also assume *liability*, an accepted treatment recommendation will always solve the consumer's problem, which yields utility V. If a consumer rejects, both the consumer and the expert receive an outside option σ_C and σ_E, respectively.

2.1 Payoffs

Payoff for experts

Given our assumptions of *liability* and *verifiability*, experts can exploit asymmetric information by overtreatment only. Experts might recommend an expensive treatment despite a cheap treatment being sufficient to solve a consumer's problem. Experts might overtreat if the mark-up for an expensive treatment exceeds a cheap treatment's mark-up. We thus set $p_s - c_s = y_s > y_m = p_m - c_m$ with $y_m > 0$ such that treating a consumer always yields positive profits. We denote the expert cheating probability by $\beta \in [0, 1]$. In addition, we assume that experts strictly prefer to treat consumers rather than falling back on the outside option, which gives $\sigma_E < y_m$.

Payoff for consumers

We assume that consumers suffer from a greater loss in utility given an untreated serious problem rather than an untreated minor one, such that $\sigma_{cm} > \sigma_{cs}$. Consumers strictly prefer to be treated with a suitable treatment rather than falling back on the outside option as $V - p_s > \sigma_{cs}$ and $V - p_m > \sigma_{cm}$. While consumers are unable to identify ex ante the severity of their problem, the different outside options imply the ex post revelation of an untreated problem's severity.[3] Due to the liability of experts, consumers will accept minor treatment recommendations with certainty. Expensive treatment recommendations will only be accepted with a certain probability $\gamma \in [0,1]$. Consumers are assumed to be better off when rejecting an expensive treatment given a minor problem, which gives $V - p_s < \sigma_{cm}$. Table 1 summarizes the payoff structure of the game.

		treatment		
		expensive	cheap	rejected
problem	serious ($\omega = s$)	$V - p_s$, $p_s - c_s$	-, -	σ_{cs}, σ_E
	minor ($\omega = m$)	$V - p_s$, $p_s - c_s$	$V - p_m$, $p_m - c_m$	σ_{cm}, σ_E

Table 1: Summary of (consumer, expert) payoffs

2.2 Information

Before visiting an expert, consumers receive a signal on the severity of their problem. A consumer's type $t \in T = \{h,l,n\}$ is referred to as high risk if he receives a bad signal, as low risk if he receives a good signal and as neutral if he receives an uninformative signal. The probability of receiving a bad signal is given by $q \in [0,1]$. Note that in our model a market comprises either uninformed ($t = n$) or informed consumers ($t = (l,h)$) only. We exclude the case where experts are confronted with informed and uninformed consumers at the same time. Therefore, q always determines the proportion of high-risk consumers and $(1-q)$ the proportion of low-risk consumers in a market. Signal precision - denoted by ϕ - can be written as

$$\phi \equiv Pr(t = h|\omega = s) = Pr(t = l|\omega = m) \in \left[\frac{1}{2}, 1\right) \quad (1)$$

[3] We feel that these specific outside options are crucial to model actual conditions on expert markets. Consumers can observe their utility from a treatment without knowing whether this solution was optimal. However, they are also able to observe their loss in utility for an untreated problem. Consider e.g. a person that feels sick: while the person might be unsure about the severity of the illness ex-ante, they will definitely learn about the severity of the illness when it remains untreated.

We can derive the following posterior beliefs after consumers have learned about their type

$$\alpha_l \equiv Pr(s|l) = \frac{\alpha(1-\phi)}{(1-\alpha)\phi + \alpha(1-\phi)} \quad (2)$$

$$\alpha_h \equiv Pr(s|h) = \frac{\alpha\phi}{\alpha\phi + (1-\alpha)(1-\phi)} \quad (3)$$

$$\alpha_n \equiv Pr(s|n) = \alpha. \quad (4)$$

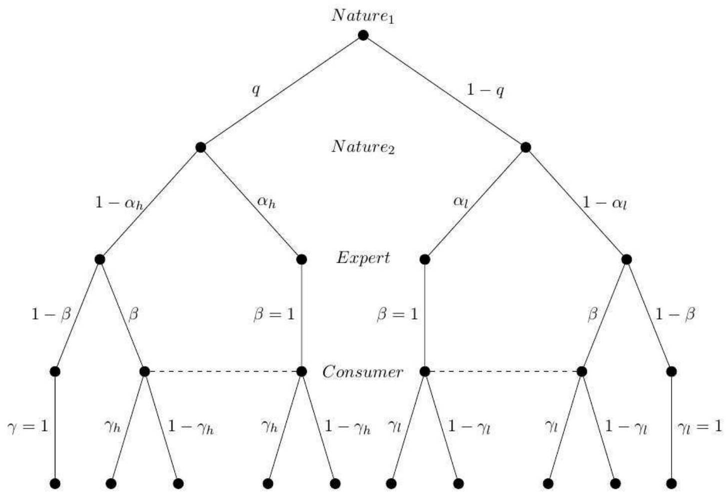
We exclude the trivial case where consumers always accept expensive treatment recommendations by

$$V - p_s < \alpha_t \sigma_{cs} + (1-\alpha_t)\sigma_{cm}, \quad (5)$$

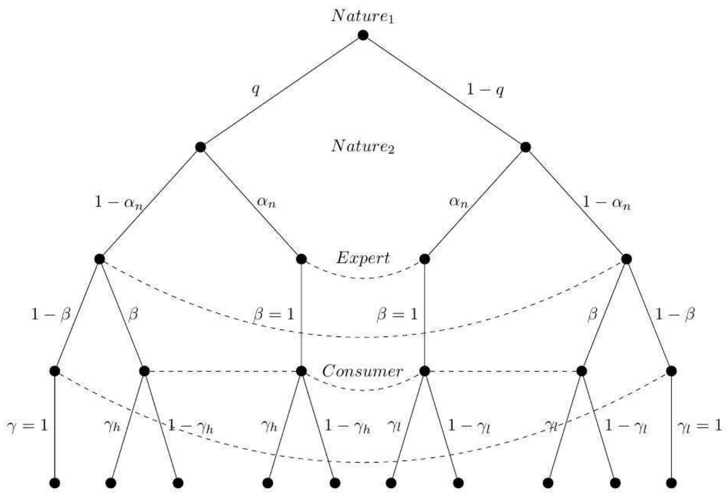
which gives

$$\alpha_t < \frac{V - p_s - \sigma_{cm}}{\sigma_{cs} - \sigma_{cm}}. \quad (6)$$

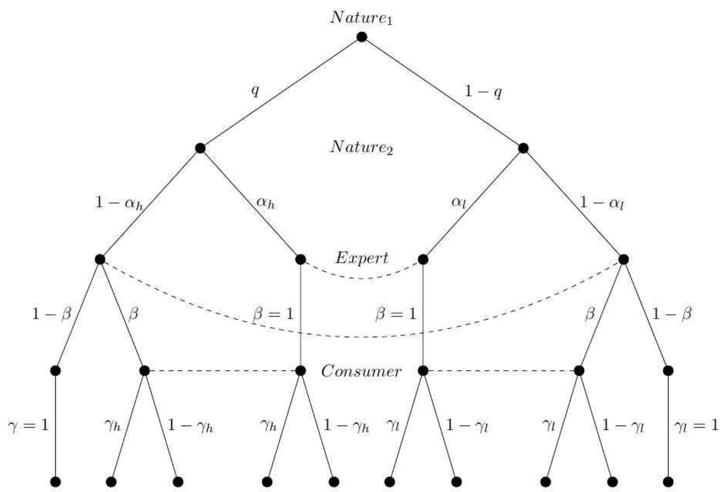
While experts can perfectly infer a consumer's problem, expert behavior depends on their ability to observe consumer signals. Therefore, we derive the equilibrium behavior conditional on consumer types and experts' ability to observe the underlying signals. The game trees in figure 1 illustrate our settings of the game, which we subsequently analyze in further detail.



(a) open consumer signal



(b) no consumer signal



(c) hidden consumer signal

Figure 1: Settings of the game

2.2.1 Equilibrium: signal observed by experts

In this section, we derive equilibria when consumers receive a signal that is observed by experts. If a signal is informative, consumers receiving a bad signal have a higher probability of suffering from a serious problem with $\alpha_h > \alpha$ compared with consumers who receive a good signal with $\alpha_l < \alpha$. If signals are uninformative, neutral consumers face a probability between those two values with $\alpha_n = \alpha$.
We assume symmetric equilibria where experts choose a uniform cheating probability β_t and consumers accept an expensive treatment recommendation, depending on their type, with uniform probability γ_t. Considering pure strategy equilibria, we derive a full circular argument.

Lemma 1: *There are no pure strategy equilibria in the game with consumer signals that are open to experts.*

Proof of Lemma 1: Consider experts with strategy $\beta = 0$, i.e. they never cheat. In this case, consumers anticipate this honest behavior and always accept an expensive treatment recommendation with $\gamma = 1$, since $V - p_s > \sigma_{cs}$. However, when $\gamma = 1$, experts have the incentive to always cheat and thus optimally play $\beta = 1$, which gives a consumer payoff of $V - p_s$. Consumers choosing $\gamma = 0$ instead - i.e. rejecting expensive treatment recommendations with certainty - become better off given the expected payoff $\alpha_t \sigma_{cs} + (1-\alpha_t)\sigma_{cm}$ due to our assumption in (6). We thus arrive at full circle implying that there are no pure strategy equilibria.

□

We now turn to mixed strategy equilibria.

Lemma 2: *In the mixed strategy equilibrium with experts observing consumer signals, consumers of type $t \in T = \{h, l, n\}$ accept an expensive treatment recommendation with probability $\gamma_t^* = \frac{p_m - c_m - \sigma_E}{p_s - c_s - \sigma_E}$. Experts cheat consumers conditional on their type t with probability $\beta_t^* = \frac{\alpha_t (V - p_s - \sigma_{cs})}{(1-\alpha_t)(p_s + \sigma_{cm} - V)}$.*

Proof of Lemma 2: An expert following a mixed strategy recommends an expensive treatment to a consumer suffering from a minor problem with probability $0 < \beta < 1$. We can formulate the necessary condition defining a consumer's accepting probability of an expensive treatment that makes an expert indifferent between an honest and a dishonest treatment recommendation by

$$\gamma_t (p_s - c_s) + (1-\gamma)\sigma_E = p_m - c_m \tag{7}$$

$$\Rightarrow \gamma_t^* = \frac{p_m - c_m - \sigma_E}{p_s - c_s - \sigma_E}. \tag{8}$$

For a consumer of type $t \in T$ to be indifferent between accepting and rejecting an expensive treatment recommendation, experts must choose a corresponding cheating probability

$$\beta_t^* = \frac{\alpha_t(\sigma_{cs} + p_s - V)}{(1-\alpha_t)(V - p_s - \sigma_{cm})}. \tag{9}$$

If an expert cheats with a probability strictly greater [lower] than β_t^*, a consumer of type t always rejects [accepts] an expensive treatment recommendation. Moreover, β_t^* increases with a consumer's belief about having a serious problem α_t. Since experts observe consumer signals, they are able to choose different strategies for each consumer type. Hence, in the mixed strategy equilibrium, experts discriminate consumers according to their type-specific cheating tolerance. High-risk consumers are cheated with a greater probability than neutral and low-risk consumers, with the latter being cheated the least. Therefore, Hyndman and Ozerturk (2011) interpret β_t^* as the tolerance of consumers of type t towards being cheated. Since $\alpha_h > \alpha_n > \alpha_l$, we obtain

$$\beta_h^* > \beta_n^* > \beta_l^*. \tag{10}$$

A consumer's reaction function - conditional on an expert's β - is given by

$$\gamma_t \in \begin{cases} 1 & \text{if } \beta < \beta_t^* \\ \gamma_t^* & \text{if } \beta = \beta_t^* \\ 0 & \text{if } \beta > \beta_t^*. \end{cases} \tag{11}$$

□

In the mixed strategy equilibrium, an expert's expected profit is given by

$$\pi_E(\alpha_t, \gamma_t^*, \beta_t^*) = \alpha_t \gamma_t^*(p_s - c_s) + \alpha_t(1-\gamma_t^*)\sigma_E + (1-\alpha_t)\beta_t^*\gamma_t^*(p_s - c_s) + (1-\alpha_t)\beta_t^*(1-\gamma_t^*)\sigma_E + (1-\alpha_t)(1-\beta_t^*)(p_m - c_m), \tag{12}$$

which can be rearranged by plugging in $\gamma_t^* = \frac{p_m - c_m - \sigma_E}{p_s - c_s - \sigma_E}$ to obtain

$$\pi_E^{open} = p_m - c_m, \tag{13}$$

where the superscript *open* refers to the case of an open signal observed by the expert. A consumer's expected profit is given by

$$\pi_{Ct}(\alpha_t, \gamma_t^*, \beta_t^*) = \alpha_t \gamma_t^*(V - p_s) + \alpha_t(1-\gamma_t^*)\sigma_{Cs} + (1-\alpha_t)\beta_t^*\gamma_t^*(V - p_s) + (1-\alpha_t)\beta_t^*(1-\gamma_t^*)\sigma_{Cm} + (1-\alpha_t)(1-\beta_t^*)(V - p_m). \tag{14}$$

which can be rearranged by plugging in $\beta_t^* = \frac{\alpha_t(V-p_s-\sigma_{Cs})}{(1-\alpha_t)(p_s+\sigma_{Cm}-V)}$ to obtain

$$\pi_{Ct}^{open}(\alpha_t) = V - p_m - \alpha_t \frac{(\sigma_{cs}-\sigma_{cm})(p_s-p_m)}{V-p_s-\sigma_{cm}}. \tag{15}$$

Since high-risk consumers are cheated more often, a consumer's expected payoff decreases in the risk α_t of having a serious problem.

2.2.2 Equilibrium: signal not observed by experts

In this section, we assume that experts are no longer able to observe consumer signals. Consequently, experts are incapable of discriminating consumers with respect to their type-specific cheating tolerance. However, experts learn about the fractions of high- and low-risk consumers in the market as they observe q, where $(1-q)$ gives the fraction of low risk consumers due to the absence of neutral-risk consumers.

Again, we arrive at a full circular argument in trying to identify pure strategy equilibria.

Lemma 3: *There are no pure strategy equilibria in the game with consumer signals that are hidden to experts.*

Proof of Lemma 3: see proof of Lemma 1.

□

In the mixed strategy equilibrium, consumers' acceptance strategy γ_t^* - as derived in (7) - makes the expert indifferent between cheating and being honest. However, since experts are no longer able to discriminate with respect to consumer types, they have to choose a uniform strategy β for all consumers.

If the expert sets $\beta > \beta_t^*$ [$\beta < \beta_t^*$], consumers of type t will reject [accept] an expensive treatment recommendation with certainty. Choosing $\beta < \beta_l^*$ [$\beta > \beta_h^*$] would make all consumers strictly accept [reject] an expensive treatment recommendation, which contradicts equilibrium behavior as described in the proof of Lemma 1.

This leaves the expert with two equilibria choices for β. By setting $\beta = \beta_h^*$, the expert causes all low-risk consumers to reject expensive treatment recommendations with certainty. This would be optimal if the more frequent cheating of high-risk consumers (over-)compensates the loss from low-risk consumers always rejecting expensive treatment recommendations. For this consideration to hold true, an expert's expected profit by setting $\beta = \beta_h^*$ needs to be greater than her expected profit by choosing $\beta = \beta_l^*$, i.e. $\pi_E^h(\beta_h^*, \gamma_h^*, \gamma_l) > \pi_E^l(\beta_l^*, \gamma_h, \gamma_l^*)$. If the expert chooses $\beta = \beta_l^*$ instead, all high-risk consumers would accept an expensive treatment recommendation with certainty and low risk-consumers, respectively, with γ_l^*.

Lemma 4: *If consumer information is hidden, experts always choose the low-risk consumer equilibrium with* $\beta = \beta_l^* = \frac{\alpha_l(\sigma_{cs}+p_s-V)}{(1-\alpha_l)(V-p_s-\sigma_{cm}}$. *In this scenario, high-risk consumers always accept expensive treatment recommendations, i.e.* $\gamma_h = 1$, *and low-risk consumers play their mixed strategy equilibrium, i.e.* $\gamma_l^* = \frac{p_m-c_m-\sigma_e}{p_s-c_s-\sigma_e}$.

Proof of Lemma 4: If experts choose $\beta = \beta_h^* = \frac{\alpha_h(\sigma_{cs}+p_s-V)}{(1-\alpha_h)(V-p_s-\sigma_{cm}}$, all low-risk consumers reject an expensive treatment recommendation all of the time, i.e. $\gamma_l = 0$. By contrast, all high-risk consumers choose their mixed strategy equilibrium, i.e. $\gamma_h^* = \frac{p_m-c_m-\sigma_e}{p_s-c_s-\sigma_e}$. In this scenario an expert's expected payoff is given by

$$\pi_E^h(\alpha_l,\beta_h^*) = q(p_m-c_m)+(1-q)[\alpha_l\sigma_e+(1-\alpha_l)\beta_h\sigma_e+(1-\alpha_l)(1-\beta_h)(p_m-c_m)], \quad (16)$$

which gives

$$\pi_E^h(\alpha_l,\beta_h^*) = p_m-c_m-(1-q)[(p_m-c_m-\sigma_e)(\alpha_l+\beta_h^*-\alpha_l\beta_h^*)]. \quad (17)$$

If experts choose instead $\beta = \beta_l^* = \frac{\alpha_l(\sigma_{cs}+p_s-V)}{(1-\alpha_l)(V-p_s-\sigma_{cm}}$ all high risk-consumers accept an expensive treatment recommendation with certainty, i.e. $\gamma_h = 1$. By contrast, all low-risk consumers choose their mixed strategy equilibrium, i.e. $\gamma_l^* = \frac{p_m-c_m-\sigma_e}{p_s-c_s-\sigma_e}$. In this scenario, an expert's expected payoff is given by

$$\pi_E^l(\alpha_h,\beta_l^*) = (1-q)(p_m-c_m)+q[\alpha_h(p_s-c_s)+(1-\alpha_h)\beta_l(p_s-c_s)+(1-\alpha_h)(1-\beta_l)(p_m-c_m)], \quad (18)$$

which gives

$$\pi_E^l(\alpha_h,\beta_l^*) = p_m-c_m+q[(p_s-c_s-p_m+c_m)(\alpha_h+\beta_l^*-\alpha_h\beta_l^*)]. \quad (19)$$

Experts would choose the high-risk equilibrium if and only if $\pi_E^h(\alpha_l,\beta_h^*) > \pi_E^l(\alpha_h,\beta_l^*)$. However, since we assume $0 < q < 1$, $\pi_E^h(\alpha_l,\beta_h^*)$ will never exceed $\pi_E^l(\alpha_h,\beta_l^*)$.

□

This property of our model stems from an unfavorable outside option for experts in case of treatment rejections, making contracting - even by providing a cheap treatment - experts' predominant objective if they are unable to observe consumer types. Consequently, experts prefer the low-risk cheating equilibrium to maximize their number of realized contracts.

In this equilibrium, low-risk consumers' expected profit is given by

$$\pi_{Cl}^{l}(\alpha_l) = V - p_m - \alpha_l \frac{(\sigma_{cs} - \sigma_{cm})(p_s - p_m)}{V - p_s - \sigma_{cm}}. \tag{20}$$

High-risk consumers' expected profit is given by

$$\pi_{Ch}^{l}(\alpha_h, \beta_l^*) = V - p_m - (\alpha_h + \beta_l^* - \alpha_h \beta_l^*)(p_s - p_m). \tag{21}$$

2.3 Welfare

In the following, we analyze how consumer information affects welfare as measured by the expected aggregate income and the distribution of income between consumers and experts.

2.4 Expert Welfare

No signal vs. open signal

If there is no consumer information - i.e. consumers receive an uninformative signal observed by experts - all consumers are of the same type $t = n$ and experts' cheating probability becomes β_n^*, as described in (9). In case of informative signals observed by experts, consumers are cheated with respect to their types and they choose their corresponding mixed strategy acceptance probability $\gamma_t = \gamma_t^*$, as shown in (7). The expected income of experts becomes equivalent for *no signal* and *open signal* and is given by (13). We can write

$$\Delta\pi_E = \pi_E^{noSignal}(\beta_n^*) - \pi_E^{open}(\beta_t^*) = 0. \tag{22}$$

Therefore, experts are indifferent between no consumer information at all and consumer information that they can observe. Note that this result is independent of the actual share q of high-risk consumers in the market.

Hidden signal vs. open signal

Given hidden signals, experts have to choose a uniform cheating probability $\beta_t = \{\beta_l^*, \beta_h^*\}$. In this case, they cannot discriminate consumers along their cheating tolerance. According to Lemma 4, experts always opt for $\beta = \beta_l^*$ and their expected payoff becomes (19). The expected change in income in comparing an open and hidden signal can be written as

$$\Delta\pi_E^l = \pi_E^l(\beta_l^*) - \pi_E^{open}(\beta_t^*). \tag{23}$$

By inserting and rearranging, we obtain

$$\Delta\pi_E^l = q[(p_s - c_s - p_m + c_m)(\alpha_h + \beta_l^* - \alpha_h\beta_l^*)] > 0. \tag{24}$$

Since $p_m - c_m < p_s - c_s$, the expression is strictly positive and the expert is better off by not observing consumer signals and being able to commit to the low-risk cheating equilibrium. In addition, the proportion of high-risk consumers in the market determines the shift in income, with a higher proportion the more intense it is.

2.5 Consumer Welfare

No signal vs. open signal

Consumers receiving either an uninformative signal or a signal observed by experts accept an expensive treatment recommendation with probability γ_t^* in the mixed strategy equilibrium, which yields them an expected payoff as described in (15). As outlined above, consumer payoff decreases with the probability of having a serious problem, i.e. α_t. Therefore, the difference in payoff depends on a consumer's type and can be written as

$$\Delta\pi_C = \pi_C^{noSignal}(\beta_n^*) - \pi_C^{open}(\beta_t^*). \tag{25}$$

which gives

$$\Delta\pi_C = (\alpha_t - \alpha_n)\frac{(\sigma_{cs} - \sigma_{cm})(p_s - p_m)}{V - p_s - \sigma_{cm}}. \tag{26}$$

As this ratio is strictly positive, high-risk consumers are worse off with an open signal since $\alpha_h > \alpha_n$. By contrast, low-risk consumers are better off with an open signal since $\alpha_l < \alpha_n$. Consequently, welfare is redistributed by consumer information from high- to low-risk consumers.

Hidden signal vs. open signal

Consumers receiving a signal that is not observed by experts are cheated with a uniform probability $\beta_t = \{\beta_l^*, \beta_h^*\}$ and react according to their reaction function described in (11). By experts always setting β_l^*, all high risk-consumers accept an expensive treatment recommendation with certainty, i.e. $\gamma_h = 1$. Their expected income is given by (21). By contrast, low-risk consumers accept an expensive treatment recommendation with γ_l^* and their expected payoff amounts to (20). Since low-risk consumers' expected profit is equivalent for an open and hidden signal, we can assess the difference in income by considering high-risk consumers only. We arrive at

$$\Delta\pi_C^l = \pi_{Ch}^l(\gamma_h, \beta_l^*) - \pi_{Ct=h}^{open}(\alpha_h), \tag{27}$$

which gives

$$\Delta\pi_C^l = q[(p_s - p_m)\frac{(V - p_s - \sigma_{cs})(\alpha_l - \alpha_h)(1 - \alpha_h)}{(1 - \alpha_l)(V - p_s - \sigma_{cm})}] > 0. \tag{28}$$

Since $\alpha_l - \alpha_h < 0$, as well as $V - p_s - \sigma_{cm} < 0$, both the numerator and denominator are negative. Consequently, the expression becomes strictly positive, implying that (high-risk) consumers become better off by hiding consumer information.

2.6 Overall Welfare

Overall welfare is the aggregate of consumer and expert income. Both depend on the share of high-risk consumers in the market and the availability of consumer information.

No signal vs. open signal

As previously mentioned, there are no differences for experts in terms of welfare when comparing the scenarios of *no signal* and *open signal*. However, overall welfare depends on the share of high-risk consumers in the market q, since consumers' payoff decreases with the probability of having a serious problem as shown in (15). We can write

$$\Delta\pi_1 = \pi_C^{noSignal}(\beta_n^*) - \pi_C^{open}(\beta_t^*), \tag{29}$$

which gives

$$\Delta\pi_1 = \frac{(\sigma_{cs} - \sigma_{cm})(p_s - p_m)}{V - p_s - \sigma_{cm}}[q\alpha_h + (1-q)\alpha_l - \alpha_n)]. \tag{30}$$

With the fraction being strictly positive, whether market participants are better or worse off as a whole, depends on the actual values of q, α_h and α_l.

Hidden signal vs. open signal

In case of hidden signals, experts choose the uniform cheating probability $\beta = \beta_l^*$ and consumers react according to their reaction function given by (11). As previously mentioned, both (high-risk) consumers and experts are better off in this scenario when consumer information is hidden. This results from contracting generally being more favorable for experts. Experts abstain from causing low-risk consumers to always reject expensive treatment recommendations by choosing the low-risk cheating equilibrium and benefit from increased contracting rates. We can write

$$\Delta\pi_2 = \pi^l(\beta_l^*) - \pi^{open}(\beta_t^*), \tag{31}$$

which gives

$$\Delta\pi_2 = \pi_E^l(\beta_l^*) - \pi_E^{open}(\beta_t^*) + \pi_{Ch}^l(\alpha_h, \beta_l^*) - \pi_{Ct=h}^{open}(\alpha_h) > 0. \quad (32)$$

The expression is strictly positive, implying that overall welfare increases in this scenario by hiding consumer information.

3 Experimental design

3.1 Overview of the game and parameterization

Our experimental design builds upon the theoretical framework and the assumptions described above. Each session features one market for expert services comprising twelve subjects, similar to Mimra et al. (2014). Subjects are randomly assigned to the role of an expert or consumer. The roles remain constant throughout the eight periods of the game. Payoffs are denominated in ECU, accumulated over periods and paid at the end of the experiment, where ECU 1 converts to EUR 0.60.

Consumers suffer either from a serious or minor problem. The probability of having a serious problem depends on a consumer's type, i.e. $\alpha_n = 0.5$ without an informative signal and either $\alpha_l = 0.2$ with a good signal or $\alpha_h = 0.8$ with a bad signal. Consumers are matched with one expert who recommends an expensive or a cheap treatment. Experts learn about a consumer's problem at no cost. Experts can either recommend an expensive treatment which costs her $c_s = 4$ or cheap treatment which costs her $c_m = 3$. Consumers can accept this treatment recommendation and pay $p_s = 8$ for an expensive treatment or $p_m = 5$ for a cheap treatment. An accepted expensive treatment solves both serious and minor problems, whereas a cheap treatment only solves minor problems. If a consumer's problem is solved, he earns $V = 10$. As we assume liability, given a serious problem an expert is obliged to recommend an expensive treatment. Accordingly, if a consumer accepts a treatment recommendation, his problem will be solved with certainty. If a problem remains untreated - as a consumer rejects the expert's recommendation - the consumer as well as the expert earn an outside option. For a consumer, the outside option depends on the severity of his problem, i.e. $\sigma_{cs} = 1.6$ in case of a serious problem and $\sigma_{cm} = 4$ in case of a minor one. An expert's outside option is independent of a consumer's problem and amounts to $\sigma_E = 1$.

According to the strategy method, experts recommend a treatment for each of the six consumers in every period. Due to liability, experts only choose a treatment recommendation for the hypothetical case that a consumer suffers from a minor problem. Experts observe the relevant information for each consumer, i.e. a consumer's likelihood of suffering from a minor or serious problem, treatment prices and costs. Decisions are taken by checking radio buttons. However, one expert is matched with only one consumer at the end of a period, and hence we assume

monopolistic experts. In order to avoid reputational concerns, the presentation of each consumer - i.e. the position at which each consumer is displayed on the screen - is randomly determined in each period (Dulleck et al. 2011).
The experts' decision screen is shown in figure 2.

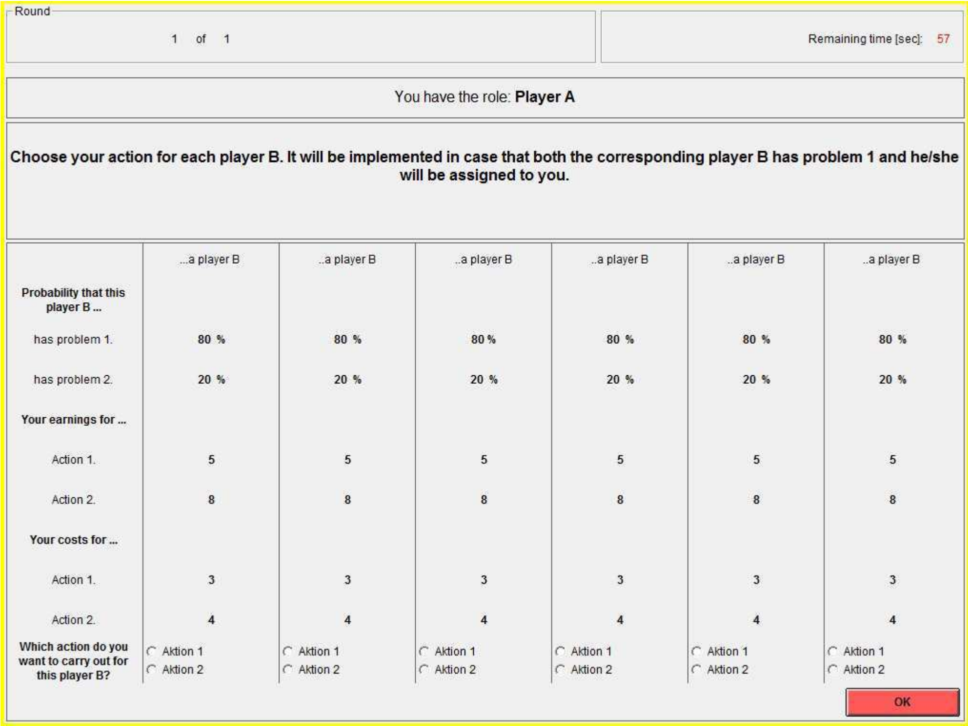


Figure 2: Expert decision screen

3.2 Treatment conditions

We implement three experimental treatment conditions that differ in terms of consumer information and experts' ability to observe this information.

noSignal: Consumers do not receive any informative signal about their likely problem and the market comprises uninformed consumers ($t = n$) only. The probability of having a serious problem is given by the ex-ante probability $\alpha_n = 0.5$.

openSignal: Consumers receive an informative signal before visiting an expert. Consumers are of either high ($t = h$) or low risk ($t = l$). High-risk consumers face a $\alpha_h = 0.8$ chance of suffering from a serious problem, whereas for low-risk consumers $\alpha_l = 0.2$. Experts observe these signals.

hiddenSignal: Consumers receive an informative signal before visiting an expert. Consumers are of either high ($t = h$) or low risk ($t = l$). High-risk consumers face a $\alpha_h = 0.8$ chance of suffering from a serious problem, whereas for low-risk consumers $\alpha_l = 0.2$. Experts do not observe these signals.

3.3 Course of the game

Each period of the game comprises six stages.

1. In *openSignal* and *hiddenSignal* each consumer is randomly selected to be of either high- or low-risk type by receiving an informative signal that updates their probability to suffer from a serious problem. In *noSignal*, all consumers receive the same uninformative signal.

2. Experts decide how to treat each of the six consumers given the hypothetical case that they suffer from a minor problem. In *openSignal*, experts can identify a consumer's type, whereas they cannot observe the type in *hiddenSignal*. Experts can choose to either overtreat a consumer by recommending an expensive treatment or act honestly by recommending a cheap treatment.

3. Each consumer is randomly matched to one expert. Based on the type-specific probabilities, it is randomly determined whether a consumer actually has a minor or serious problem.

4. Consumers suffering from a serious problem are assigned an expensive treatment recommendation in any case due to the liability assumption. Consumers suffering from a minor problem are assigned the matched expert's treatment recommendation.

5. Consumers observe the assigned treatment recommendation and decide to accept or reject.

6. If a consumer accepts, the recommendation with associated payoffs is implemented. If a consumer rejects, both the expert and consumer are paid according to their outside option. Each subject's payoff from the current period and the cumulative payoff are displayed.

3.4 Procedure

For *noSignal* / *openSignal* / *hiddenSignal*, there were 8/8/7 sessions with 96/96/84 participants. Experiments were conducted with a standard subject pool across disciplines in the Laboratory of Behavioral Economics at the University of Goettingen; using ORSEE (Greiner 2015) and z-Tree (Fischbacher 2007). The sessions lasted about 40 minutes, whereby subjects earned EUR 11.50 on average.

4 Hypotheses

In this section, we insert our experimental parameters to our theoretical framework to obtain hypotheses about subjects' behavior and the overall market outcome. Table 2 provides an overview of the expected parameter values.

	β	β_h^*	β_l^*	γ^*	γ_h	γ_l	π_E	π_C	π_{Ch}	π_{Cl}
noSignal	0.2	-	-	0.5	-	-	2.0	3.2	-	-
openSignal	-	0.8	0.05	-	$0.\overline{3}$	$0.\overline{3}$	2.0	-	2.12	4.28
hiddenSignal	0.05	-	-	-	1	$0.\overline{3}$	2.9	-	2.29	4.28

Table 2: Theoretical predictions

Since there is no equilibrium for experts to restrain from cheating, we expect them to overtreat consumers partially to increase their monetary payoff. Experts with knowledge about consumer information are able to adjust their treatment recommendations such that consumers are discriminated conditional on their type-specific cheating tolerance. Therefore, we expect experts to more frequently cheat high- rather than low-risk consumers in *openSignal*. We further expect neutral-risk consumers to be cheated less frequently than informed high-risk consumers and - conversely - more frequently than informed low-risk consumers. In case consumer information is hidden for experts, we expect experts to opt for the low-risk cheating equilibrium, i.e. $\beta = \beta_l^* = 0.05$.

Hypothesis 1 ("expert behavior")

H1a) Experts engage in cheating with and without consumer information.

H1b) Experts cheat high-risk consumers more often compared with neutral-risk consumers.

H1c) Experts cheat low-risk consumers less often compared with neutral-risk consumers.

H1d) Experts opt for the low-risk cheating probability when consumer information is hidden.

Given an observable signal, we expect that consumers' acceptance probability remains constant if they learn about their risk type, given that experts should adjust their cheating probability. In case of a hidden signal, low-risk consumers are expected to put forth the acceptance probability, whereas high-risk consumers react to the uniform cheating probability by always accepting expensive treatment recommendations.

Hypothesis 2 ("consumer behavior")

H2a) Consumers accept expensive treatment recommendations with the same probability when there is no consumer information and with an open signal.

H2b) Consumers receiving an open signal show an acceptance probability for expensive treatment recommendation independent of their specific risk type.

H2c) High-risk consumers accept all expensive treatment recommendations when consumer information is hidden, whereas low-risk consumers show the same probability to accept without or with observable consumer information.

Since there is an equal proportion of high- and low-risk consumers in the market with $q = 0.5$ and corresponding symmetric probabilities of serious problems of $P(\omega = s|t = h) = \alpha_h = 0.8$ as $1 - \alpha_h = \alpha_l = 0.2$, there should be no difference in aggregate income due to open signals when compared to no consumer information. However, we expect a redistribution of income from high- to low-risk consumers. According to our theoretical predictions, in case the signal becomes hidden, we expect an increase in experts' and high-risk consumers' welfare. Since low-risk consumers' welfare should remain constant, we expect an overall increase in welfare when consumer signals are hidden.

Hypothesis 3 ("welfare")

H3a) Overall welfare remains constant if observable consumer information is introduced.

H3b) If consumer information is hidden to experts, overall welfare increases due to more contracts between high-risk consumers and experts.

H3c) High-risk consumers benefit from introducing observable information, while low-risk consumers generate less income.

5 Results

We analyze our experimental data according to the structure of our hypotheses: first, we investigate expert cheating; second, we investigate consumer acceptance; and third, we reach an overall conclusion by deriving aggregate income conditional on the availability of consumer information. Unless mentioned otherwise, all tests are carried out treating one market, i.e. each group of six consumers or six experts interacting in a session, as one independent observation only. Therefore, we control for reputation building and other intra-group dynamics despite the random matching protocol applied in each period.

5.1 Expert behavior

Recall that all experts choose a treatment recommendation for the hypothetical case of consumers suffering from a minor problem. Figure 3 depicts expert cheating across treatments and periods.

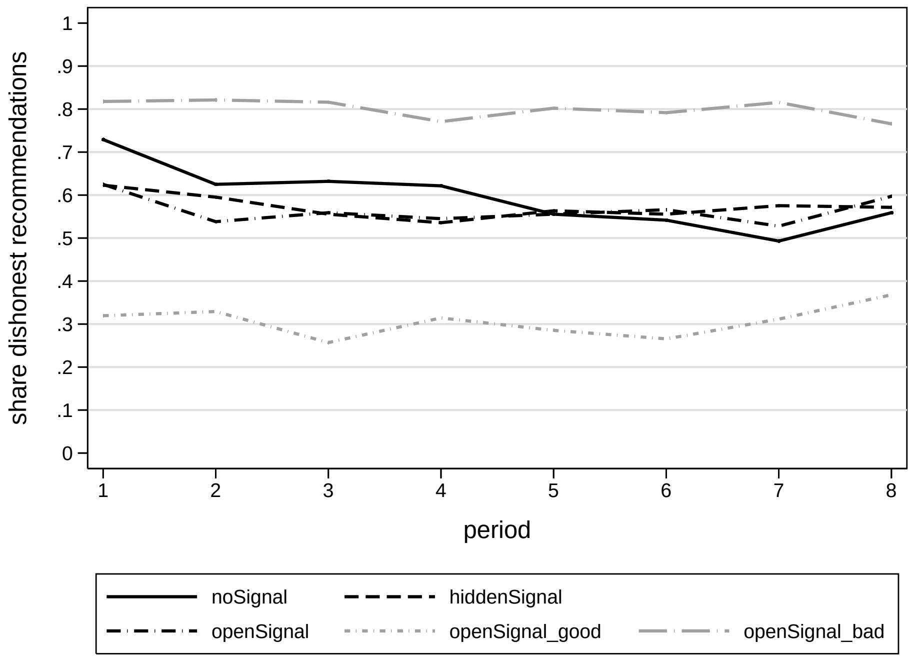


Figure 3: Experts' dishonest treatment recommendations

For all treatments, there is a considerable fraction of dishonest treatment recommendations, which is rather constant over time. In *noSignal/openSignal/hiddenSignal* the average share of dishonest recommendations amounts to 0.59/0.56/0.57, which gives strong evidence in support of H1a. On average, experts tend to cheat much more frequently than predicted by theory when there is no consumer information ($0.59 > \beta_n = 0.2$) or hidden consumer information ($0.57 > \beta_l^* = 0.05$). We further hypothesized (H1b/H1c) that consumers in *open signal* will be cheated according to their cheating tolerance, which holds true as the fraction of dishonest recommendation in case of bad signals amounts to 0.8 ($= \beta_h^*$) and only 0.31($> \beta_l^* = .05$) in case of good signals. Both are significantly different from the fraction cheated when there is no additional consumer information (Wilcoxon-Rank-Sum-test: for high risk $z = -2.100$ and $p = .0357$; for low risk $z = 3.046$ and $p = .0023$) and when there is hidden consumer information (Wilcoxon-Rank-Sum-test: for high risk $z = 2.083$ and $p = .0372$; for low risk $z = -2.893$ and $p = .0038$). However, there is no difference in cheating behavior between *noSignal* and *hiddenSignal*, which contradicts H1d (WRS test: $z = .753$ and $p = .4515$). To assess expert behavior in further detail, we address cheating at the individual level in figure 4.

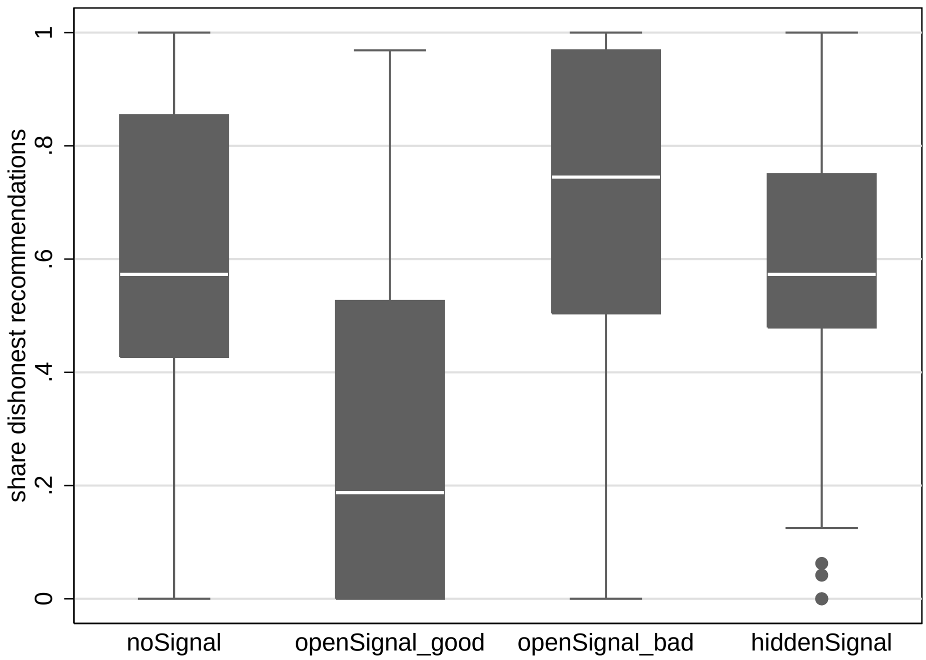


Figure 4: Distribution of experts' dishonest treatment recommendations

It becomes evident that cheating behavior is quite homogeneous. The fraction of approximately 60% dishonest treatment recommendations in *noSignal* and *hiddenSignal* do not stem from experts either cheating all the time or never cheating; rather,they apply a mixed strategy of cheating with a certain probability. There are 14.58/2.08/7.14% (4.17/4.17/7.14%) of experts who always (never) overtreat their consumers.

Result 1: Experts tend to cheat much more often than suggested by theory when there is no additional consumer information. Experts adjust their treatment recommendations to account for differences in consumers' cheating tolerance. Experts do not adjust their treatment recommendations in terms of whether there is no consumer information or hidden consumer information.

5.2 Consumer behavior

Figure 5 depicts the fraction of realized contracts, the equivalent to accepted recommendations subject to experts' treatment recommendations.

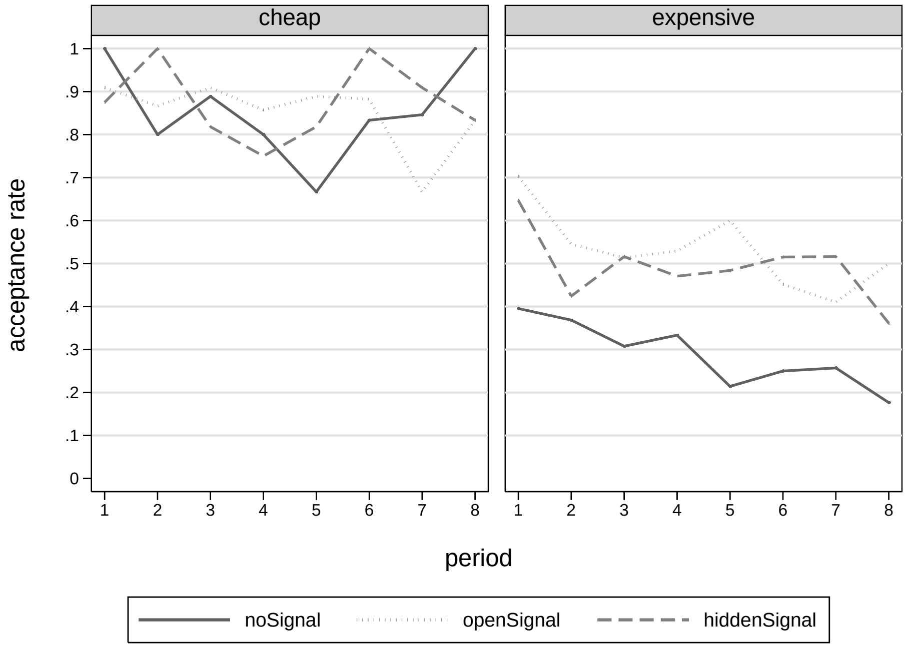


Figure 5: Consumer acceptance conditional on treatment recommendations

The acceptance rate in case of cheap treatment recommendations is close to - but not perfectly - 1 and there is neither a trend over time nor a substantial difference across treatments (Kruskal-Wallis test: $\chi^2 = 3.113$ and $p = .2109$). For expensive treatment recommendations, in *noSignal* there are significantly more rejections compared to *openSignal* and *hiddenSignal* (Kruskal-Wallis test: $\chi^2 = 14.048$ and $p = .009$), which contradicts H2a. Without additional consumer information, consumers are more reluctant to accept expensive treatment recommendations than suggested by theory ($.29 < \gamma^* = .5$). Therefore, consumers with additional information tend to accept expensive treatment recommendations significantly more often, which can be analyzed in further depth by differentiating acceptance with respect to the signals received as shown in figure 6.

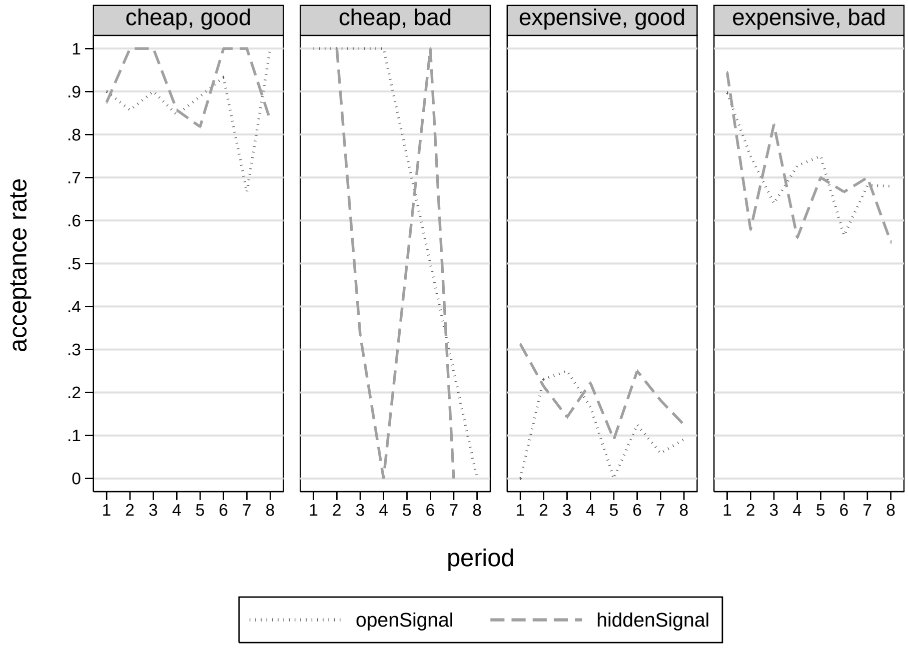


Figure 6: Consumer acceptance conditional on treatment recommendations and signals

Optimal behavior suggests that cheap treatment recommendation should always be accepted. As expected, we find no specific pattern with respect to good or bad signals. However, it has to be considered that there are very few observations for consumers who received a cheap treatment recommendation and a bad signal, which explains the peaks in graphs.[4]

In case of expensive treatment recommendations, there is an evident difference with respect to consumers' received signals. Recall that we expected that the probability of accepting an expensive treatment remains constant over treatments with $\gamma_{l/h} = 0.\overline{3}$, except for high-risk consumers in *hiddenSignal* who should always accept an expensive treatment recommendation (cp. table 2).

If consumers received a bad signal, they are substantially more willing to accept a serious treatment recommendation (Wilcoxon matched-pairs signed-ranks test: for *openSignal* $z = -2.521$ and $p = .0117$; for *hiddenSignal* $z = -2.366$ and $p = .0180$), which detrimentally contradicts H2b, where we hypothesized that the acceptance probability is independent of the specific risk type when there is an open signal. However, there are no differences due to signals being open or hidden to the expert (WRS test: for good signal $z = 1.158$ and $p = .2467$; for bad signals $z = 0.926$ and $p = .3545$). This has to be interpreted as mixed evidence with respect to H2c.

[4]In *openSignal* this pattern occurred only eight times, in *hiddenSignal* ten times.

Result 2: Consumers tend to frequently reject expensive treatment recommendations if they do not receive additional information. Good signals are associated with very low levels of acceptance, while bad signals are associated with very high levels of acceptance. Whether the signal is open or hidden to the expert has no influence on this basic pattern.

5.3 Welfare

We rely on aggregate income to evaluate welfare. Recall that aggregate income is maximal if a consumer's problem is solved by the appropriate treatment. Furthermore, in terms of aggregate income, it is superior that a consumer with a minor problem is assigned an expensive treatment rather than no treatment at all. Consequently, welfare increases in the number of contracts and the frequency of contracts featuring the appropriate treatment. Figure 7 details the fraction of realized contracts and the fraction of contracts featuring the appropriate treatments.

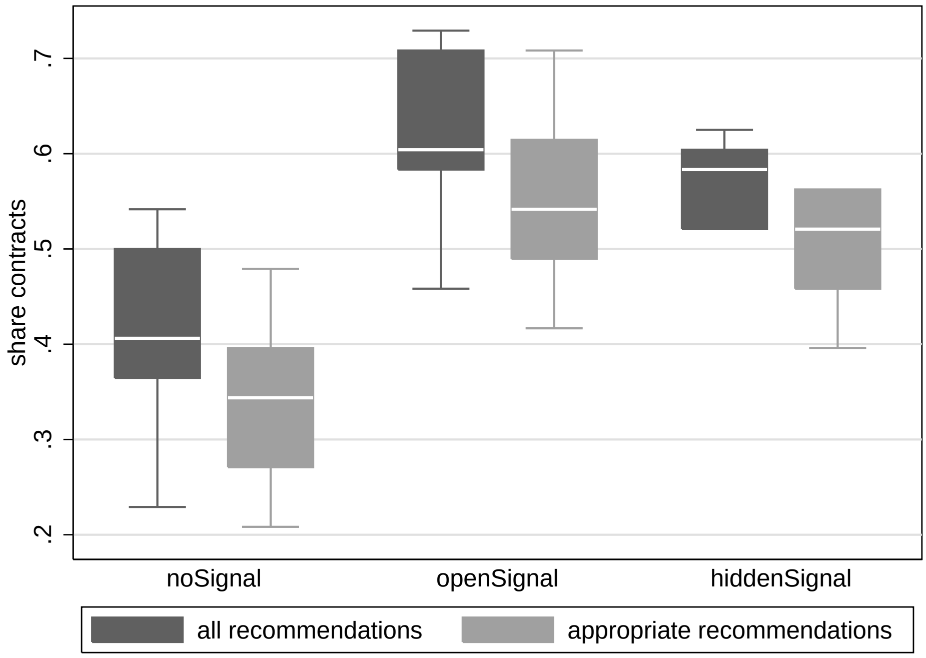
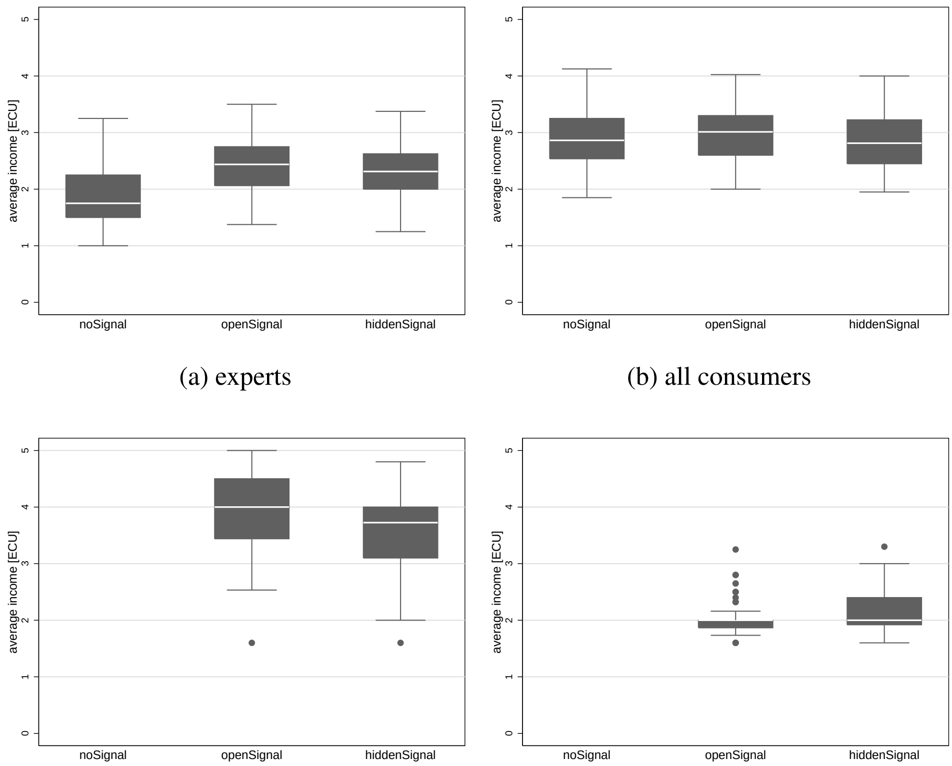


Figure 7: Contracts realized

Contradicting H3a, the fraction of realized contracts - with and without an appropriate treatment - is substantially lower when there is no additional consumer information and thus welfare is superior when introducing consumer information (Kruskal-Wallis test: for fraction of contracts $\chi^2 = 12.682$ and $p = .0018$). The median fraction of realized contracts drops by about 20 p.p. in the absence of consumer information. Differences between open and hidden consumer information are rather small and contracts tend to be less frequent in *hiddenSignal*, which contradicts H3b. Average aggregate income on the market level for *noSignal/openSignal/hiddenSignal* amounts to ECU 228/257/249. 70/40/44% of serious problems remain untreated in *noSignal/openSignal/hiddenSignal*.

Result 3: Aggregate income is higher when additional consumer information is introduced, independent of whether experts are informed. Accordingly, there are more contracts realized and appropriate treatments are more frequent. Contradicting our predictions by theory, hidden signals tend to reduce welfare.

Figure 8 presents the distribution of income over roles and treatments conditional on received signals.



(a) experts

(b) all consumers

(c) low-risk consumers

(d) high-risk consumers

Figure 8: Distribution of income

The box-plots of 8a and 8b confirm our previous findings. Bad signals make consumers accept expensive treatment recommendations much more frequently, which disproportionately benefits experts. This is due to the difference between an expert's outside option $\sigma_E = 1$ and her income for carrying out an expensive treatment $p_s - c_s = 8 - 4 = 4$, which is equal as for the consumer receiving $\sigma_{Cm} = 4 > V - p_s = 10 - 8 = 2$ at best or at worst $\sigma_{Cs} = 1.6$. Therefore, as predicted by our theory (cp. table 2), it is the experts - rather that consumers - who predominantly benefit from additional consumer information as bad signals substantially

reduce consumers' reluctance to accept expensive treatment recommendations.
Moreover, we expected a redistribution of income to the detriment of high-risk consumers when there is observable consumer information. As indicated by 8c and 8d, consumers earn significantly more when they are of low risk (Wilcoxon matched-pairs signed-ranks test: for *openSignal* $z = 2.521$ and $p = .0117$; for *hiddenSignal* $z = 2.366$ and $p = .0180$), which supports H3c. Furthermore, in *openSignal* consumers earn less (more) when they are of high (low) risk when compared to uninformed consumers (WRS test: for uninformed vs. high risk $z = 3.046$ and $p = .0023$; for uninformed vs. low risk $z = -3.361$ and $p = .0008$). The same holds true in *hiddenSignal* (WRS test: for uninformed vs. high risk $z = 1.967$ and $p = .0491$; for uninformed vs. low risk $z = -3.240$ and $p = .0012$).

Result 4: Experts benefit from introducing consumer information due to the substantial reduction in consumers' reluctance to accept expensive treatment recommendation when receiving bad signals. For both open and hidden signals, low-risk consumers benefit from additional consumer information, while high-risk consumers are worse off.

6 Conclusion

In the literature, there is plenty of research about markets for expert services, in which ex-ante consumer information has not gained much attention. However, providing additional consumer information is among the most prominent proposals to overcome the inefficiencies due to asymmetric information. Therefore, we have investigated how consumers receiving an informative yet noisy signal before visiting an expert influences experts' cheating behavior, consumers' acceptance probabilities and overall welfare in a market for expert services. In our theoretical model, we introduced three different treatments in which consumers receive either (1) an uninformative signal, (2) an informative signal observed by experts or (3) an informative signal hidden to experts. We built closely on the incentive structure by Pitchek and Schotter (1987), i.e. there is a difference in consumer welfare conditional on the severity of an untreated problem. Our model enables us to derive behavioral hypotheses on the effects of additional consumer information, which we tested experimentally.
We find that experts' likelihood of fraudulent behavior - i.e. recommending an expensive treatment when a cheap one would be sufficient to solve a consumer's problem - is influenced by ex-ante consumer information observed by experts. Our novel lab results thus confirm the findings of Lee and Soberon-Ferrer (1997), Fong (2005), Schneider (2012) as well as Balafoutas et al. (2013) that experts tend to cheat consumers conditional on their identifiable characteristics, which is given by the risk type in our setting determined by received signals. Our data shows that experts cheat high-risk consumers significantly more often than low-risk

consumers, which supports the hypothesis by Hyndman and Ozerturk (2011) that hiding bad signals might be beneficial to consumers. Our results thus indicate that - in contrast to common sense - uninformed consumers are not the most likely victims of fraudulent behavior; rather, it is the informed high-risk type. In contrast to our theoretical predictions, we do not find any influence on experts' fraudulent behavior by hiding consumers' signals compared to the case of no ex-ante consumer information.

Moreover, our results show a significant influence of consumers' information on their acceptance probability - i.e. their likelihood of market entry - for expensive treatments. Without additional information, consumers show substantially lower rates of acceptance than suggested by theory. This might be due to consumers hoping for a minor problem, in which case the outside option doubles their income in comparison to accepting an expensive treatment. In the worst case, they fall back on the outside option and suffer from a serious problem, which only reduces their income by 20%. Accordingly, the risk in monetary terms of an untreated serious problem compared to a treated one was quite small. Based on this consideration, it is quite surprising that consumers substantially change their behavior and show very high acceptance probabilities when receiving bad signals. Since consumers condition their behavior on the received signals, more serious problems are treated appropriately with informative signals. However, there is no evidence that consumers account for experts' ability to observe their signals as they behave similarly in terms of accepting probabilities in case of hidden and open signals.

Aggregate income increases when there is additional consumer information. This stems from consumers' tendency to reject expensive treatment recommendation if they do not distinctively receive a bad signal. In case of open signals, low cheating probabilities associated with good signals meet low acceptance rates of expensive treatments, whereas bad signals are associated with high cheating probabilities and high acceptance rates. This results in more realized contracts and more consumer problems are solved appropriately. In case of hidden signals, experts tend to cheat as if there was no consumer information, while consumers with bad signals show higher acceptance rates of expensive treatments. Again, there are more contracts realized and especially more serious problems solved.

In sum, markets for expert services generate superior levels of overall welfare when there is additional ex-ante consumer information. This is driven by experts benefiting from more frequently accepted expensive treatment recommendations implying more realized contracts and less outside option payments. Whether consumers benefit or not crucially depends on risk types, where low-risk consumers are better off and high-risk consumers are worse off when introducing additional consumer information.

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Appendix A - Instructions

General Information about the Experiment

There are twelve participants and eight periods in the experiment. The course of a period is the same for all periods. In each period, new pairs of two participants will be matched randomly. Each pair comprises exactly one player with role A and one player with role B. In general, the experiment is about player B having a problem in each period, which can be solved by an action of player A. In the beginning of the experiment, it will be randomly determined whether you are playing as player A or player B: therefore, half of all participants will be playing as player A and the other half as player B. The roles remain fixed throughout the course of the experiment.

Your profit in this experiment is calculated in credits with **1 credit = 0.60 Euro**. At the end of the experiment, your income will be converted from credits into Euros and paid to you. Your final payoff depends on your own and other participants' decisions. At the end of each period you will see your own payoff from this period, as well as how much you earned over all periods up to this point.

In every period player B has exactly one problem: either problem 1 or problem 2. The problem will again be determined randomly in each period for each player B, independently and with a fixed probability. [T1: The probability of player B having problem 1 is 50%. Consequently, the probability of player B having problem 2 is also 50%.] [T2,T3: The probability of player B having either problem 1 or problem 2 depends on his type: either type 1 or type 2.] Player B's type is again randomly determined in each round. The relations are displayed in the following table:

Player B with...	Probability of having Problem 1	Probability of having Problem 2
Type 1	80 %	20 %
Type 2	20 %	80 %

The table can be read in the following way:

- If you are a player B type 1, your probability of having problem 1 is 80% and the probability of having problem 2 is 20%.
- If you are a player B type 2, your probability of having problem 1 is 20% and the probability of having problem 2 is 80%.]

As a player B you will never be informed which problem you actually have. [T2,T3: You are merely informed about your probability of having either problem 1 or problem 2.]

General Course of the Experiment

The course for each of the eight periods is identical and summarized in the following:

1. Player A decides which actions she wants to take.
2. Pairs are matched randomly and each player B's actual problem is determined.
3. Player B decides whether he wants to accept player A's proposed action.
4. Each player is informed about her/his payoff.

In the following, each stage is explained in detail. Additionally, player A's and player B's payoffs are summarized on the last page of the instructions.

1. Player A's Action

Player A's task is to solve player B's problem through her action. In each round, she can choose between two distinct actions: action 1 or action 2. The selectable actions for player A depend on player B's actual problem in each round:

- **If player B has problem 1**, player A can choose both action 1 or action 2. Both actions solve the problem but lead to different costs and earnings for player A and player B.
- **If player B has problem 2**, player A has to solve this by choosing action 2.

Each action leads to different **earnings for player A**, which have to be paid by player B (player B's payoff will be described later):

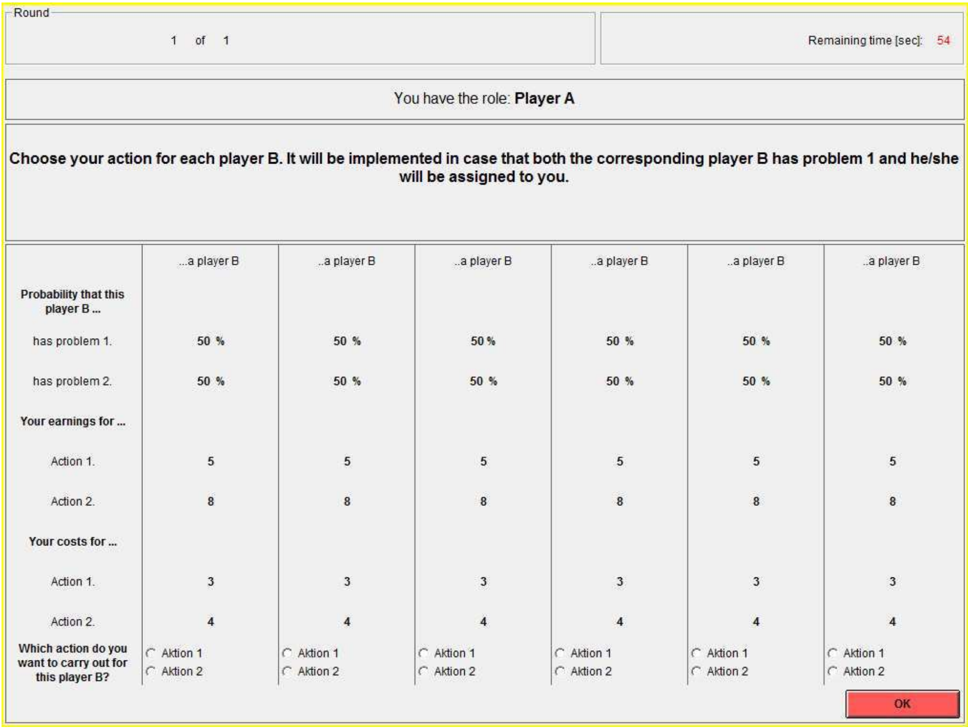
- Action 1: Player B pays 5 credits to player A.
- Action 2: Player B pays 8 credits to player A.

In addition, each action causes different **costs for player A**:

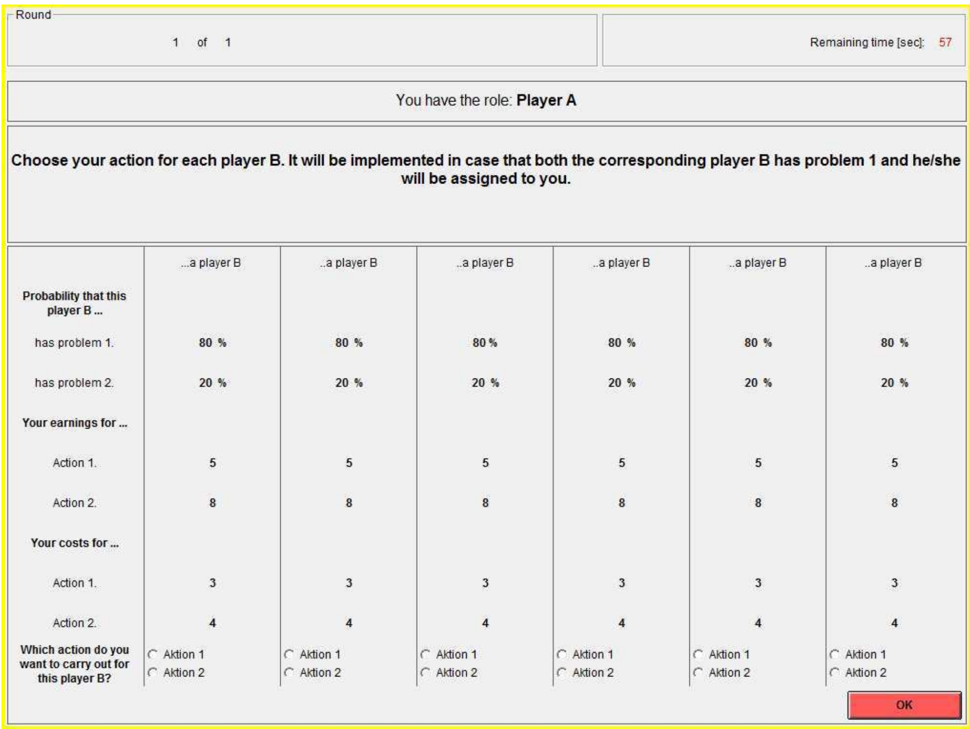
- Action 1 induces costs of 3 credits.
- Action 2 induces costs of 4 credits.

In the beginning of each round, player A decides for each of the six players B, which action she wants to carry out for each of them. At this time, player A does not know about the player B with which she will be matched in this round. **Consequently, player A decides in advance how she wants to behave towards each player B in case she will be matched to him.** The position where all player Bs are represented on the screen will be randomly determined in each round. For illustrative purposes, player A’s decision screen is presented below:

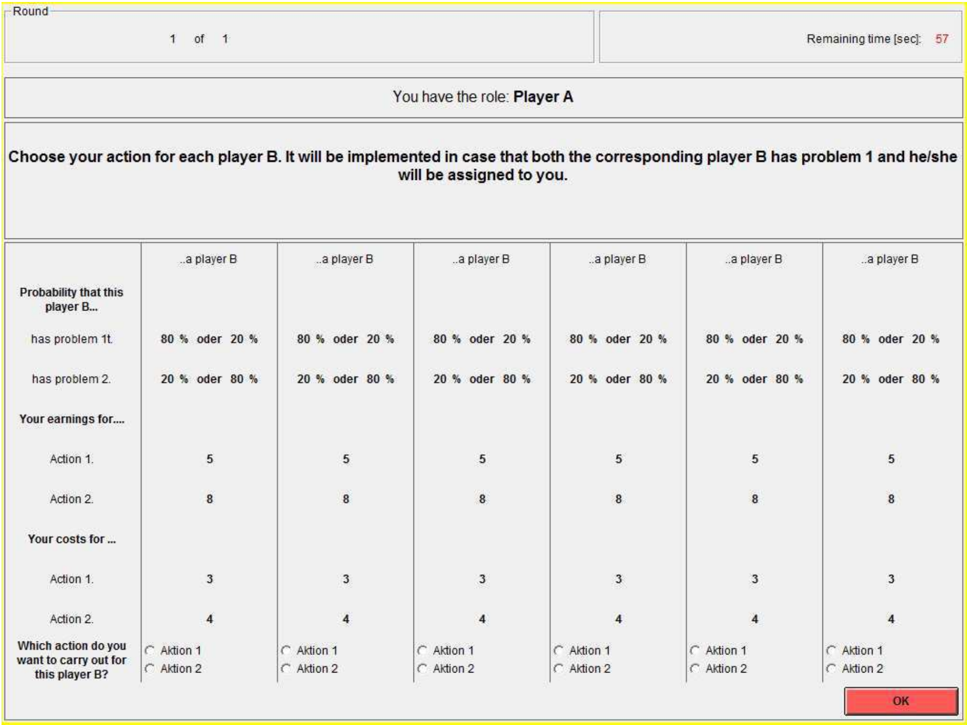
T1:



T2:



T3:


Round

1 of 1

Remaining time [sec]: 57

You have the role: **Player A**

Choose your action for each player B. It will be implemented in case that both the corresponding player B has problem 1 and he/she will be assigned to you.

	..a player B	..a player B	..a player B	..a player B	..a player B	..a player B
Probability that this player B...						
has problem 1t.	80 % oder 20 %	80 % oder 20 %	80 % oder 20 %	80 % oder 20 %	80 % oder 20 %	80 % oder 20 %
has problem 2.	20 % oder 80 %	20 % oder 80 %	20 % oder 80 %	20 % oder 80 %	20 % oder 80 %	20 % oder 80 %
Your earnings for....						
Action 1.	5	5	5	5	5	5
Action 2.	8	8	8	8	8	8
Your costs for ...						
Action 1.	3	3	3	3	3	3
Action 2.	4	4	4	4	4	4
Which action do you want to carry out for this player B?	Aktion 1 / Aktion 2	Aktion 1 / Aktion 2	Aktion 1 / Aktion 2	Aktion 1 / Aktion 2	Aktion 1 / Aktion 2	Aktion 1 / Aktion 2

OK

[T1,T2: Player A can observe each player B's probability of having either problem 1 or problem 2.] [T3: Player A cannot observe players B's probabilities of having either problem 1 or problem 2. Therefore, player A remains uninformed about whether a specific player B is either type 1 or type 2. However, she knows that a player B's probability of being either type 1 or type 2 is 50%.] Moreover, player A's costs and earnings for action 1 and action 2 are shown on the screen. At the bottom of the screen, player A has to choose which action she wants to carry out for each player B. For each player B a decision has to be made.

Note that in case player B has problem 2, player A has to carry out action 2. If the player B who is actually matched to her has problem 2, action 2 will be assigned automatically to this player A. **Therefore, the decision made by player A is only implemented if the matched player B has problem 1!**

2. Matching and Determining Player B's Problem

After all players A chose their actions for a period, each player B is randomly matched with one player A. **The random matching is carried out in each round.**

Subsequently, for each player B it is determined - according to his type and the corresponding probabilities - whether he has problem 1 or problem 2.

- **If a player B has problem 1**, the matched player A's chosen action is presented to him. This can be either action 1 or action 2.
- **If a player B has problem 2**, action 2 is presented to him automatically, since player A has no choice in this case than to carry out action 2.

Since player B does learn about his actual problem, he cannot infer - in case action 2 was chosen for him - whether player A chose action 2 or if it was assigned automatically.

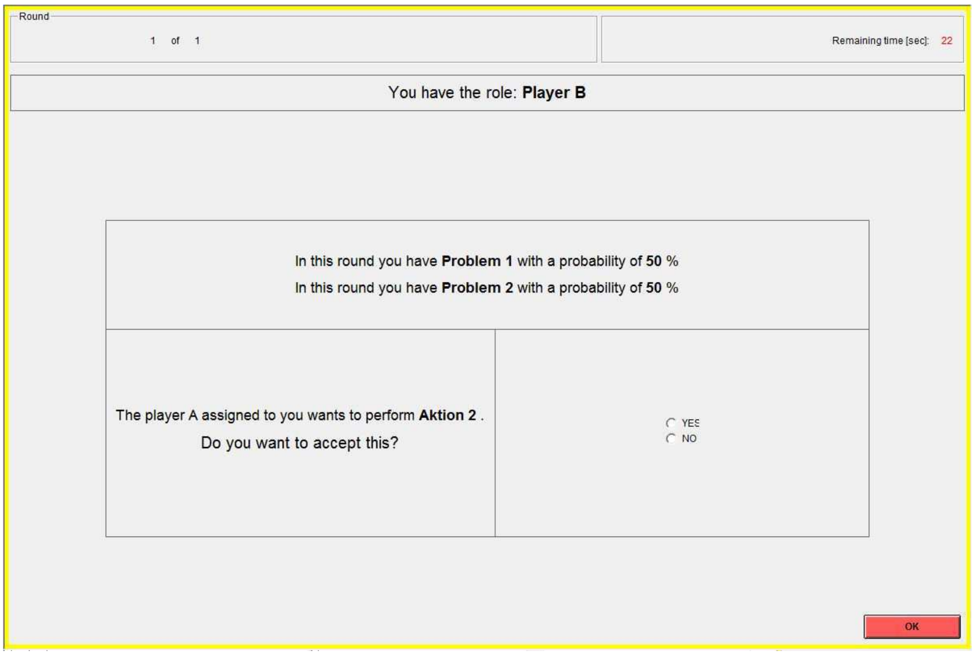
3. Player B's Action

Player B knows whether action 1 or action 2 was chosen for him and learned about the underlying probabilities of having either problem 1 or problem 2 in this period. However, he is not informed about his actual problem. Player B now decides whether to accept or reject the chosen action.

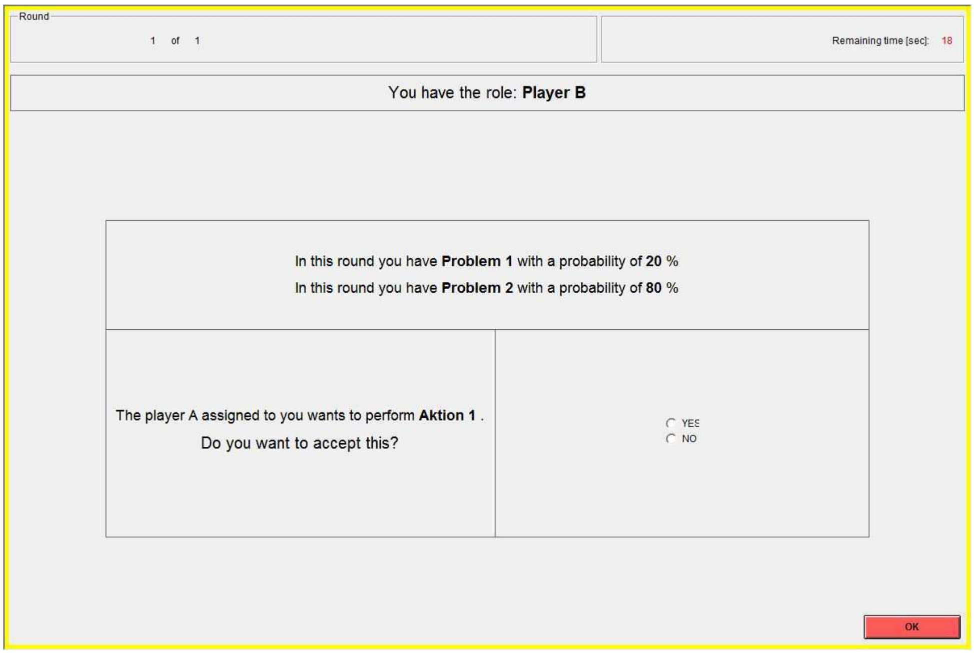
- **If player B accepts the action**, it will be implemented. Player B receives a payment of **10 credits**. These 10 credits are reduced by the amount that player B has to pay to his matched player A for her action. Player A's earnings are reduced by the cost of the action.
- **If player B rejects the action**, both players receive an outside payment. Player A's outside payment amounts to 1 credit. The amount of player B's outside payment depends on whether he had problem 1 (= 4 credits) or problem 2 (= 1.6 credits) in this period.

For illustrative purposes, player B's decision screen is presented below:

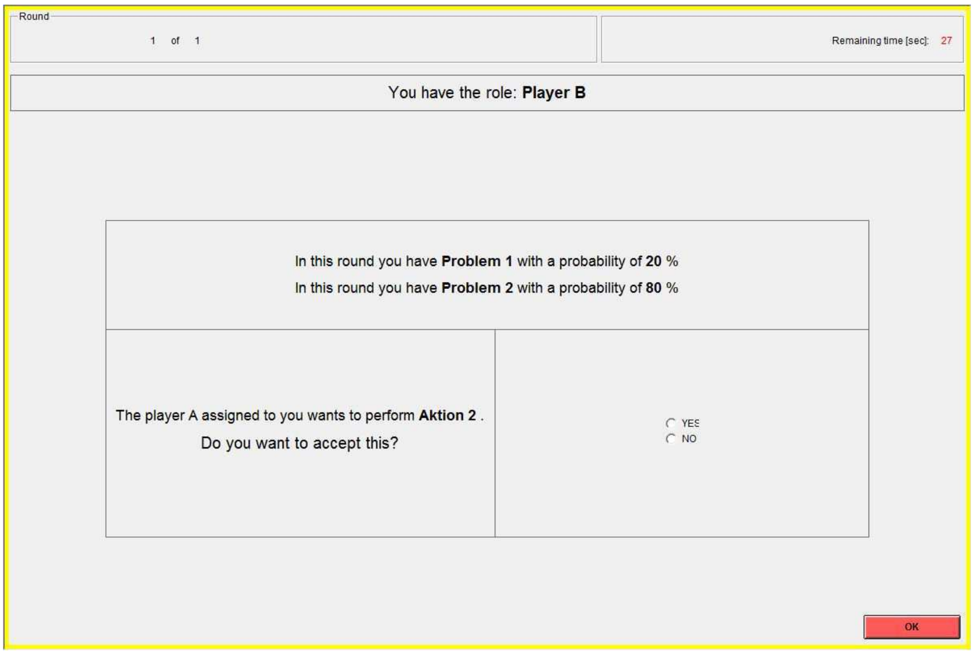
T1:


Round
1 of 1
Remaining time [sec]: 22
You have the role: **Player B**
In this round you have **Problem 1** with a probability of **50** %
In this round you have **Problem 2** with a probability of **50** %
The player A assigned to you wants to perform **Aktion 2** .
Do you want to accept this?
YES
NO
OK

T2:


Round
1 of 1
Remaining time [sec]: 18
You have the role: **Player B**
In this round you have **Problem 1** with a probability of **20** %
In this round you have **Problem 2** with a probability of **80** %
The player A assigned to you wants to perform **Aktion 1** .
Do you want to accept this?
YES
NO
OK

T3:



A period ends after player B's decision. At the end of each round...

- **each player A is informed** which actual problem her matched player B had, which action she took accordingly and whether this player B accepted or rejected this action.
- **each player B is informed** which action was chosen for him and whether he accepted or rejected the action, but not which problem he actually had.

At the end of each period, player A and player B are informed about their payoffs from this period and how much they have earned over all periods up to this point.

Payoff Summary

The payoffs for player A and player B depend on their choices within the matched pair.
Player A's payoff for each period:

- If the matched player B accepts the action:
  Payoff = earnings from action - costs from action
- If the matched player B rejects the action:
  Payoff = outside payment = 1 credit

Player A's payoffs are summarized in the following table:

	Accepted Action 1	Accepted Action 2	Rejection
Player B has Problem 1	2 credits	4 credits	1 credit
Player B has Problem 2	-	4 credits	1 credit

Player B's payoff for each period:

- If the action of the matched player A is accepted:
  Payoff = 10 credits - player A's earnings for the action
- If the action of the matched player A is rejected and player B had problem 1:
  Payoff = outside payment = 4 credit
- If the action of the matched player A is rejected and player B had problem 2:
  Payoff = outside payment = 1.6 credits

Player B's payoffs are summarized in the following table:

	Accepted Action 1	Accepted Action 2	Rejection
Player B has Problem 1	5 credits	2 credits	4 credit
Player B has Problem 2	-	2 credits	1.6 credit

The payoffs from each period will be summed up and paid out at the end of the experiment.

Chapter 5

EFFECTS OF QUALIFICATION IN EXPERT MARKETS WITH PRICE COMPETITION AND ENDOGENOUS VERIFIABILITY

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with Kilian Bizer

Author contribution:

Tim Schneider: 90 percent

Kilian Bizer: 10 percent

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Effects of Qualification in Expert Markets with Price Competition and Endogenous Verifiability

Tim Schneider[*†] *and Kilian Bizer*[*]

Abstract

We investigate a market in which experts have a moral hazard problem because they need to invest in costly but unobservable effort to identify consumer problems. Experts have either high or low qualification and can invest either high or low effort in their diagnosis. High skilled experts are able to identify problems with some probability even with low effort while low skilled experts here always give false recommendations. Experts compete for consumers by setting prices for diagnosis and service. Consumers can visit multiple experts, which enables an endogenous verifiability of diagnosis. We show that with a sufficient number of high skilled experts, stable second-best and perfectly non-degenerate equilibria are possible even with flexible prices, although they depend on transactions costs being relatively low. By contrast, with a small share of high skilled experts in the market, setting fixed prices can be beneficial for society.

Keywords: credence goods; expert market; moral hazard; qualification; competition; second opinions

JEL: L10; D82; D40

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1 Introduction

Expert markets are a constant feature in economic transactions: visiting a doctor or a car mechanic, taking a cab in a foreign city, engaging financial services or home improvement contracts are suitable examples. The issue underlying all these interactions is given by consumers' uncertainty about the specifics of their demand, being only aware that some service or good is required. Commonly, consumers are neither able to identify ex ante on their own the severity of their problem nor ex post - in the case of a solved problem - which service actually solved it. With consumers lacking the necessary knowledge, they have to visit an expert for diagnosis and treatment. By contrast, experts can not only identify consumer problems but also determine and carry out necessary services. This particular kind of information asymmetry enables fraud, as experts might exploit their informative edge to increase their own monetary payoff at consumers' expense. This can result in either inefficiencies or market breakdowns with consumers anticipating potential fraud and refraining from contracting (Akerlof, 1970; Dulleck, Kerschbamer, 2006; Dulleck et al., 2011; Emons, 2001; Mimra et al., 2016).

Due to this potential for market failure, markets for expert services are commonly regulated by entry barriers with specific requirements like completed studies and vocational training. In most fields, it appears quite easy for consumers to identify someone as actually being an expert. By contrast, it is much more difficult to identify whether an expert is high or low skilled in comparison to colleagues. Consider, for instance, ordering a tradesman to estimate the costs for repairing a washing machine. While I can be expected to identify whether the arriving person is a mechanic per se, as I interact in a regulated market and called a professional provider, I cannot easily determine whether he is of high or low skill. In most cases, I am not aware of his individual talent, years of experience, additional training or specializations, but will only observe his recommendation for service as the result of his diagnosis. Consequently, without irrational costs and effort, in a market for expert services, consumers cannot distinguish experts of different skill, as has been previously outlined, e.g. by Emons (2001), Pesendorfer, Wolinsky (2003), as well as Feser, Runst (2015).

Experts with different skill sets vary in their ability to diagnose consumer problems. For example, 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. They show that the mechanism of multiple opinions for mitigating the information problem can solve this only partially and needs additional institutions for full efficiency. In contrast to them, we argue that the assumption of low skilled experts unanimously providing low quality in diagnosis does not capture real life circumstances. While it is plausible that there are qualitative differences in the ability to diagnose, a low skilled expert can also be expected to succeed in correctly identifying consumer problems if he is willing to invest sufficient effort. Therefore, rather than high skilled experts always giving correct recommendations and low skilled experts always giving wrong ones, a diagnosis' accuracy should depend on individuals' willingness to invest effort in it. Accordingly, a high skilled expert might provide a wrong diagnosis if he only invests minimal effort, while a low skilled expert who invests a great amount of resources can give a correct recommendation.

Most of the credence goods literature assumes that experts can determine consumers' problems perfectly at no costs (Wolinsky, 1993; Dulleck, Kerschbamer, 2006; Dulleck et al., 2011; Hyndman, Ozerturk, 2011; Mimra et al., 2016). However, this does not represent real-life circumstances, as diagnosis is actually costly for experts - at least time consuming. Experts have to choose how much effort they are willing to invest in their diagnosis: is someone only interested in faking a genuine diagnosis by presenting a plausible story or is he really concerned for consumers' well-being and willing to invest a substantial effort to make a more precise diagnosis? Due to the credence goods character, consumers are in general unable to determine experts' effort levels without irrationally high costs (Emons, 2001; Feser, Runst, 2015), which results in a moral hazard problem. This might prompt experts to underinvest in diagnosis to maximize their own utility. This, in turn, would lead to inferior service recommendations based on guesses rather than real diagnosis.

In this paper, we are primarily concerned with the moral hazard problem of experts in providing truthful but costly diagnosis, due to the unobservability of their effort choices. We examine a market with heterogeneous experts regarding their ability to identify problems, while consumers are able to verify experts' recommendations through multiple opinions. We extend the framework of Pesendorfer, Wolinsky (2003) by introducing heterogeneously-qualified experts. In accordance with Brush et al. (2017) and Norman et al. (2007), we incorporate the notion that high skilled experts have an edge in diagnosis by being able to identify consumer problems with less effort than low skilled experts. Our model allows for a more detailed view on experts' willingness to invest in costly diagnosis, consumers' willingness for contracting and how this affects overall welfare. Moreover, it enables us to provide policy implications concerning how to adapt prices for diagnosis and service to maximize overall welfare in reaction to different market conditions, i.e. experts' costs for high effort and transaction costs for consumers to visit an expert, as well as market composition, i.e. the share of high skilled experts in the market and their edge in qualification in comparison to low skilled experts. To our best knowledge, there is no other model that analyzes how qualification levels affect markets for expert services.

To introduce our model, imagine again the aforementioned tradesman scenario. In our model a consumer is in need of a service, as she notices that she has some issue, whereby she wants to get her washing machine repaired. However, she is unaware which kind of service would actually solve her problem. We model the continuum of possible services by $b \in [0,1]$. Let $V > 0$ be a consumer's utility when the problem is solved appropriately, i.e. the service carried out corresponds to b, and zero otherwise. Experts can identify consumer problems depending on their individual skill level and their effort choice. For simplification, let experts be of either high or low skill and able to only choose between high and low effort. Notice that we do not let experts decide on their recommendation strategy, implying that whether a recommendation is correct or not is being determined by an expert's effort choice and degree of qualification only. This let us also derive conclusions about experts' propensity for undertreatment, as in this case an underprovision of diagnosis due to low effort is driven only by experts having a financial incentive for it. In order to model high skilled experts' edge in diagnosis, they have some probability $y \in (0,1)$ of providing a correct diagnosis even with low effort, while low skilled experts always give a false recommendation in this case. When an expert chooses high effort, he will always give a correct recommendation irrespective of his skill. However, all experts have to incur costs $c > 0$ for high effort.

We assume a market with a finite number of N experts and M consumers. Let $a \in [0,1]$ be the share of high skilled experts in the market, which is common knowledge. Each consumer is free to visit up to N experts for diagnosis. A visited expert offers a contract comprising fees for diagnosis and service. Additionally, let $s > 0$ be the transactions costs that arise for consumers by contacting an expert. However, we assume that informing oneself about diagnosis and service costs is free and consumers only have to bear the transaction costs s in case they actually receive a diagnosis. When a consumer decides to get diagnosed, she automatically receives a service recommendation conditionally on the visited expert's effort choice and skill. Subsequently, the consumer can either buy the corresponding service or get further diagnoses to potentially confirm her first recommendation. Notice that we assume that experts can only provide services that they have formerly recommended. This design enables an endogenous verifiability of diagnosis. With the possibility to search for matching opinions consumers can verify a recommendation on their own but have to bear higher search costs in this case.

We analyze expert and consumer behavior as well as overall welfare regarding their reactions to different market compositions, i.e. the share of high skilled experts in the market a, their degree of qualification y, and market circumstances, i.e. consumer valuation V, transaction costs s and costs for high-effort choices c. We are particularly interested in experts' high effort choices and consumers' search behavior, as for the latter there is no possibility for a unique strategy to make all experts choose their mixed strategy due to heterogeneous qualification. We find that consumers will adapt their search behavior according to market composition, as they need to search for matching opinions more often to make high skilled experts choose high effort with a positive probability. However, if a is sufficiently high, there is the possibility for a second best equilibrium, in which welfare is maximized even without the intervention of a policy-maker, e.g. by fixing prices for service and diagnosis. By contrast, with a being relatively low, a stable second best equilibrium requires fixed prices as outlined by Pesendorfer and Wolinsky before. In sum, the optimal price level for service - and whether a stable second best equilibrium is possible - depends on the share of high skilled experts in the market, their degree of qualification, as well as whether prices are fixed or flexible and the amount of transactions costs consumers have to bear for diagnoses.

Related Literature

The central aspect in our model is experts' moral hazard problem to costly but unobservable diagnosis effort. In a model, where experts compete with discounters, Dulleck, Kerschbamer (2009) show that the former undertreat consumers to avoid free-riding behavior. Moreover, Bonroy et al. (2013) find that risk averse experts are less likely to invest in costly diagnosis. Pesendorfer, Wolinsky (2003) show that only with fixed prices and consumers being able to receive multiple opinions, a stable second best outcome can be realized where consumers' welfare is maximized. Furthermore, Bester, Dahm (2017) argue that by introducing unobservable subjective evaluation of consumers regarding service success, even first-best outcomes can be achieved by separating diagnosis and treatment. However, as they do not incorporate transactions costs in their model, this first-best solution needs to be seen as rather special case.

Additionally, it appears decisive whether consumers can consult more than one expert for diagnosis. Wolinsky (1993) shows that depending on the costs for visiting multiple experts this can lead to an overall welfare increase. This is in line with the results of Mimra et al. (2016), showing that the rate of overtreatment decreases significantly with the possibility of second opinions. Here, market efficiency increases depending on additional search costs. Nevertheless, in their experiment the willingness to search for second opinions was significantly lower than theory had predicted. Mimra et al. (2016) attribute this to consumers might thought that honest expert types are prevailing in the market or to consumers' risk aversion. It seems, therefore, that already the threat of second opinions might lead experts to less fraudulent behavior. However, Pesendorfer, Wolinsky (2003) show theoretically that the possibility for multiple opinions, in a market where experts decide on their effort for diagnosis, does not lead to Pareto optimal outcomes due to incentive incompatibility and transactions costs for consumers.

Another relevant institution in our model is given by price competition. Dulleck et al. (2011) show when experts compete for consumers through price setting, this drives down overall prices and increases trade volume. Additionally, in case that experts are liable, price competition has a positive effect on market efficiency. Mimra et al. (2016) confirm the price reducing effect and show that price competition significantly drives down experts' profits, shifting surplus to consumers. However, with price competition, experts seem to show more willingness for undertreatment and overcharging.

The remainder of the paper is structured as follows. Section two introduces our model. Section three presents our analysis and discusses our results and section four concludes.

2 Model

Our theoretical model builds closely on Pesendorfer, Wolinsky (2003) which we apply to the case of heterogeneously qualified experts and a limited number of players.

We assume a finite number of N experts and M identical consumers in the market. In general, consumers need some service for a problem which can be identified and treated by experts. However, an expert needs to exert effort for a correct diagnosis. We assume consumers are unable to observe experts' actual effort choices, as well as their degree of qualification and experts do not know a consumer's history, i.e. whether she has consulted other experts before her visit. Additionally, we exclude reputation as experts are not identifiable and are contacted in random order.

Consumers receive a positive payoff $V > 0$, if they purchase a service $b \in [0,1]$ matching their problem type $i \in [0,1]$, otherwise they get a payoff of zero. Since consumers do not know about their actual type i, they need to consult one or more experts. Each expert offers a contract (d, p) to consumers with d as the diagnosis costs and p as the costs of service. Experts provide diagnosis by recommending a service to consumers conditional on their effort choice. In return, consumers decide whether they are willing to accept the recommendation which would automatically lead to the execution of the recommended service. Consumers can consult up to N experts but have to bear transaction costs s for each consulted expert in addition to diagnosis costs d.

In contrast to Pesendorfer, Wolinsky (2003), we assume experts with varying degrees of qualification which affect their ability for correct diagnosis. For simplification, we assume experts are either high or low skilled. Let an expert's skill type be $q_t \in \{0,1\}$ with $t \in \{h,l\}$, where $q_h = 1$ denotes high skill and $q_l = 0$ denotes low skill. Notice that by introducing heterogeneous experts in the market, there are two dimensions which can affect market outcome:

> Firstly, there is the magnitude of how much high skilled and low skilled experts differ in their degree of qualification, i.e. to which extent high skilled experts are better in diagnosis. For our model, we assume that to diagnose a consumer, experts need to decide on their effort level $e \in \{0,1\}$ with $e = 1$ denotes high effort and $e = 0$ denotes low effort. High effort always leads to correct recommendations, regardless of the individual level of qualification. In contrast, low effort always leads to a wrong recommendation, if an expert is low skilled. If an expert is high skilled he makes a correct diagnosis by low effort with probability $y \in (0,1)$. Consequently, the variable y defines the magnitude of

the difference in qualification to which we will refer as the degree of qualification in the following. Moreover, experts do not decide over their recommendation strategy: if an expert chooses high effort, his recommendation is always correct, i.e. he recommends a service $b = i$.

Secondly, there is the share of high skilled and low skilled experts in the market. We assume a share $a \in [0,1]$ of high skilled experts and a share $1-a$ of low skilled experts.

All experts have to bear costs $c > 0$ for high effort. For simplification, we assume that low effort, as well as all services performed are free. All information about market composition and payoff functions are common knowledge across all players.

The game consists of an infinite number of periods with the following identical course:

1. Each consumer is randomly matched with one of the N experts who proposes a contract (d,p).
2. Assuming a consumer has visited $n \geq 0$ experts so far, she decides whether she will (i) accept the offered contract and get diagnosed by this expert; (ii) if $n \leq N$, visit another expert; (iii) buy the service from any expert whose diagnosis has been received previously; (iv) leave the market without purchase and/or diagnosis. With decisions (iii) and (iv) the game ends.
3. If the contract is accepted, the consumer pays the diagnosis costs d to the expert and also has to bear the transactions costs $s > 0$.
4. Each visited expert chooses his diagnostic effort $e \in \{0,1\}$. We denote the probability of experts type q_t for high diagnostic effort by $x_t \in [0,1]$.
5. Each consumer receives a recommendation conditionally on her visited expert's effort choice and skill
6. Each consumer has to decide how to proceed further (see stage 2).

In sum, a consumer's expected utility is determined by how many experts she consults for diagnosis, the offered contracts by experts and whether a potentially bought service matches her actual problem type i. Suppose a consumer has contacted n experts, her expected utility is given by

$$U(a,s,t) = \begin{cases} V - p - \sum_{j=1}^{n} d_j - ns & \text{if } a = i \\ -p - \sum_{j=1}^{n} d_j - ns & \text{if } a \neq i \\ -\sum_{j=1}^{n} d_j - ns & \text{no purchase} \end{cases} \tag{1}$$

In contrast, an expert's profit function depends on how many consumers consult him for diagnosis, his effort choices and whether some consumers are buying his service, conditional his offered contract (d,p). An expert's expected payoff who is contacted by m consumers with $r \leq m$ consumers buying his service is given by

$$\pi(c,e) = \begin{cases} m(d-ec)+rp & \text{r consumers buy service} \\ m(d-ec) & \text{any consumer buys service} \\ 0 & \text{not consulted} \end{cases} \tag{2}$$

3 Analysis

Experts cannot observe how many experts a consumer has contacted before. They maximize their expected profit by choosing their contracts (d,p) as well as their effort level $e(t) \in \{0,1\}$, conditional on their beliefs of consumers' searching strategy. According to symmetry, identically qualified experts will choose the same strategy profile $(d_t, p_t, \varepsilon_e)$ with ε_t being denoted as the probability for high diagnostic effort x_t, conditional on the offered contract (d_t, p_t).

Consumers condition their choices on experts' expected probability to choose high diagnostic effort $x_t \in [0,1]$, the share of high skilled experts in the market a, the degree of qualification of high skilled experts y, and the offered contracts (d_t, p_t). Sampling a random expert will give a consumer a correct recommendation with the following probability

$$z = x_h a + (1-a)x_l + (1-x_h)ay, \tag{3}$$

where $x_h, x_l \in [0,1]$ determine the probabilities that an expert with high or low qualification chooses high effort.

Let $f \in [0,1]$ be the probability for a consumer to stop after her first recommendation. If $f = 1$, her expected payoff is given by

$$U(z|f=1) = zV - p - (s+d). \tag{4}$$

In contrast, with probability $1-f$ a consumer searches for two matching opinions. Since a randomly sampled expert makes a correct recommendation with probability z, the expected duration for a correct diagnosis is given by $1/z$. Consequently, the expected duration for two matching recommendations is $2/z$. The underlying search and diagnosis costs for matching diagnosis are, therefore, $2(s+d)/z$. The expected utility for a consumer, in this case, is given by

$$U(z|f=0) = V - p - 2\frac{s+d}{z} + \theta. \tag{5}$$

For a consumer to enter the market in the first place, the expected payoff from either (4) or (5) need to be positive.

Lemma 1: *A consumer's best response to (d_t, p_t, x_t) will always be one of the following strategies: (i) quit without any action; (ii) get exactly one diagnosis and purchase its service; (iii) get diagnosis until two recommendations match and buy the service from one of the two experts with matching recommendations.*

Proof of Lemma 1: *see Appendix A.*

□

On the other side, experts have to decide how much effort they are willing to invest in diagnosis. For their best response, they have to build a belief about consumers' search behavior. Let B be an expert's belief about the probability that a consumer has not been diagnosed by another expert, conditional on this consumer accepting to be diagnosed by him. When an expert is consulted and decides for high diagnostic effort, he will get an expected payoff given by

$$\pi(f, B|e=1) = d_q + p_q f B + (1 - fB)\frac{p_q}{2} - c, \tag{6}$$

with fB being the probability that a consumer has not contacted another expert before and stops after the first recommendation and $(1 - fB)$ being the probability that a consumer is searching for matching opinions. We assume that in the latter case, a consumer purchases with probability $1/2$ from an expert who provides a correct recommendation, as she has no preferences regarding the sampling order.

In contrast, if a consulted expert invests low effort for diagnosis by not incurring the costs c, his expected profit is given by

$$\pi(f, q_t, B|e=0) = d_q + p_q f B + q p_q (1 - fB)\frac{y}{2}. \tag{7}$$

With low effort, an expert will only sell his service to a consumer if she is either on her first visit and stops afterwards or with probability $y/2$, if a consumer searches for matching recommendations and the expert is high skilled. For a pure best response, experts choose high effort, i.e. $e = 1$, when (6) is strictly greater than (7). In case of indifference, any $x_t \in [0, 1]$ is optimal. Notice that by introducing different degrees of qualification, high skilled experts' incentive for high diagnostic effort has decreased. This implies that in order to make high skilled experts indifferent between high and low effort, consumers need to search ceteris paribus for matching opinions more often.

3.1 Equilibria with Fixed Prices

In the first step, we assume prices to be fixed with all experts offering identical contracts (d,p). According to Pesendorfer, Wolinsky (2003), (d,p,z,f) is a fixed price equilibrium, if consumers' choices for f are optimal given (d,p,z) and experts' effort decisions $x_t \in [0,1]$ are optimal given (d,p,f) and their beliefs B. We define an equilibrium as perfectly non-degenerate when all experts choose high diagnostic effort with positive probability, i.e. $x_h, x_l > 0$. In contrast, in a degenerate equilibrium, all experts always opt for low diagnostic effort, i.e. $x_h, x_l = 0$. Furthermore, there can be a partial non-degenerate equilibrium with only low skilled experts choosing high effort.[1] As mentioned before, the expected duration of search depends on consumers' applied strategy. With probability f, a consumer stops after her first diagnosis and buys in which case the duration is one period. In contrast, with probability $1-f$, a consumer searches for matching opinions resulting in a duration of $2/z$. Consequently, the expected duration of search S for consumers is given by

$$S = f + (1-f)\frac{2}{x_h a + (1-a)x_l + (1-x_h)ay}. \tag{8}$$

For being a Bayesian fixed price equilibrium, B needs to be consistent according to f and z which is fulfilled, if it equals the inverse of the expected duration of search.

Lemma 2: *Experts' beliefs are consistent with (d,p,z,f) if and only if*

$$B = \frac{x_h a + (1-a)x_l + (1-x_h)ay}{f(x_h a + (1-a)x_l + (1-x_h)ay) + 2(1-f)} = \frac{z}{fz + (2(1-f)}. \tag{9}$$

Proof of Lemma 2: *see Pesendorfer, Wolinsky (2003).*

□

For a non-degenerate equilibrium of any kind, experts need to get an expected payoff from high effort at least equal to low effort, given by

$$d + fBp + (1-fB)\frac{p}{2} - c \geq d + fBp + q_t p(1-fB)\frac{y}{2}. \tag{10}$$

From (10) follows that $p \geq \frac{2c}{(1-q_t y)}$ needs to be fulfilled for a non-degenerate equilibrium. Notice that the less often consumers are willing to search for matching recommendations

[1] As high skilled experts demand higher searching rates for matching opinions to be indifferent in their effort choice, there is only the possibility for partial non-degenerate equilibrium with low skilled experts choosing $x_l \in]0,1]$.

and/or when experts are higher qualified, the greater needs to be experts' markup, i.e. the difference of high effort costs c and service price p, in order to attract them for high effort.

If consumers would always buy after their first recommendation, i.e. $f = 1$, (10) would not hold, since in this case $fB = 1$ and $1 - fB = 0$. Consequently, for a non-degenerate equilibrium consumers need to weakly prefer searching for matching opinions, i.e. $f < 1$. This will only be the case, if their expected payoff from (5) is at least equal to their payoff from (4), which results in

$$V - p - 2\frac{s+d}{z} \geq zV - p - (s+d). \tag{11}$$

Three market conditions for a non-degenerate equilibrium follow from (11): (i) z has to lie within a determined interval, i.e. $z \in [\underline{z}, \overline{z}]$; (ii) the costs for diagnosis and the transaction costs may not exceed a specific threshold $s + d \leq \overline{s} \equiv V(3 - 2\sqrt{2})$; (iii) consumers will only search for matching recommendations, if $N \geq \frac{2}{z}$.[2] Finally, to be willing to choose $f < 1$, consumers need to get a positive expected utility searching for matching opinions at all by

$$V - p - 2\frac{s+d}{z} > 0. \tag{12}$$

If experts would always provide correct diagnosis by high effort, consumers would never search for matching recommendations and, therefore, (10) would not hold. If experts would always choose low effort, this would be a degenerate equilibrium by definition. For $0 < x_t < 1$, (10) must hold with equality, making experts indifferent between high and low effort choice.

$$d + fBp + (1 - fB)\frac{p}{2} - c = d + fBp + q_t p(1 - fB)\frac{y}{2}. \tag{13}$$

Solving (13) for f by substituting B we can determine f^*, making experts indifferent between high and low effort

$$f^*(q_t) = \frac{1 - \frac{2c}{p(1-q_t y)}}{1 + \frac{c(z-2)}{p(1-q_t y)}}. \tag{14}$$

Since experts differ in their degree of qualification, i.e. $q_t \in \{0, 1\}$, and have a different expected utilities depending on e_t, consumers are not able to choose a uniform f making all experts indifferent at the same time. As noticed before, (14) shows that for making high skilled experts indifferent in their effort choice, consumers need to search for matching opinions more often, since $\frac{\partial f^*}{\partial q_t} < 0$. Consumers will choose f according to what yields them the highest expected payoff. Experts will react to consumers' choice depending on their degree of qualification, i.e.

[2]For detailed calculations see Appendix B.

qy, and the fixed ratio of the price for service p and the costs for high effort c. We determine f_l^* [f_h^*] as the search rate which makes low [high] skilled experts indifferent.
It is important to emphasize that in order to establish a mixed strategy equilibrium, experts need to choose their effort level in accordance to make consumers indifferent between buying after one recommendation and searching for matching opinions. Otherwise, if consumers choose a pure strategy while $p > 2c$, there cannot be a non-degenerate equilibrium. Suppose consumers would never search for matching opinions. This would make all kind of experts strictly preferring low effort. As counter, consumers would not enter the market in the first place, unless there is a very high share of extremely well qualified high skilled experts that $V - p - 2\,\frac{s+d}{z} > 0$ which we shelve for the moment. On the other side, if consumers always search for matching opinions, experts would strictly prefer high effort, as long as $p > 2c/(1-q_t y)$. As reaction, consumers would switch to never search for matching opinions with the same consequences as before. Consequently, for getting to a non-degenerate equilibrium, it is necessary that experts choose their effort according to make consumers indifferent in their search behavior.

Lemma 3: *If $x_h = 0$, low skilled experts will balance z that $z \in [\underline{z}, \overline{z}]$, 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: From (11) follows that the probability z for getting a correct diagnosis by sampling a random expert must lie in the determined interval $z = x_h a + (1-a)x_l + (1-x_h)ay \in \{\underline{z}, \overline{z}\}$. If, for example, all high skilled experts choose only low effort when $f > f_h^*$, low skilled experts in the market will balance the downshift in z, as $x_h = 0$, by increasing their own effort level. In contrast, high skilled experts will, as well, adapt their effort choice in equilibrium when all low skilled experts choose only high effort. Consequently, we can define the threshold values for x_t in reaction to a chosen f and x_{-t} by $x_t^* \in [\underline{x_t}, \overline{x_t}]$. Only if x_t^* lies within the defined interval, a non-degenerate equilibrium is possible. This adaptation will always take place as long as market composition is not too one-sided regarding the values for a and y. We can determine the threshold values by

$$\underline{x_l^*}, \overline{x_l^*} = \frac{\frac{V+d+s}{2V} - ay \pm \sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d)}{V}}}{1-a}, \tag{15}$$

and

$$\underline{x_h^*}, \overline{x_h^*} = 1 + \frac{1 - (\frac{V+d+s}{2V} \pm \sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d))}{V}}}{a(y-1)}. \tag{16}$$

Note that x_t can only take values between 0 and 1. Consequently, if x_t^* falls below or exceeds this, an adaptation of z to the equilibrium interval $z \in [\underline{z}, \overline{z}]$ becomes impossible. By extracting the necessary conditions from (15) and (16), we receive for low skilled expert adaptation

$$a(1-y) \leq 1-z, \tag{17}$$

$$ay \leq z, \tag{18}$$

and for high skilled expert adaptation

$$a(1-y) \geq 1-z, \tag{19}$$

with $z \in \{\underline{z}, \overline{z}\} = \frac{V+d+s}{2V} \pm \sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d)}{V}}$. In the following, we will refer to these equations as the adaptation conditions for high and low skilled equilibria, since they need to be fulfilled in order to make consumers choose their mixed strategy. Conditions (17) and (18) account for low skilled experts while (19) is required for high skilled ones.[3] It follows that the share a of high skilled experts in the market and their degree of qualification y has opposed effects on high skilled experts' ability to adapt their effort choice. While an increase in a increases the possibility for adaptation, an increase in y decreases it, respectively. In contrast, for low skilled experts, an increase of a decreases the possibility for adaptation. The effect of y on low skilled experts adaptation is mixed and depends on its ratio to the other parameters.

If $a(1-y) > 1-z$, low skilled experts loose their ability for adaptation. With $a(1-y) > 1-z$, only high skilled experts will be able to adapt their effort level that $z \in [\underline{z}, \overline{z}]$. This implies that at this point, there are so many high skilled experts in the market that the existing low skilled experts cannot balance $x_h = 0$ anymore. In return, high skilled experts become able to balance $x_l = 1$ which changes the possible non-degenerate equilibrium from a partial to a perfect one. However, it is important to mention that z can take at least two values in equilibrium, i.e. $z \in [\underline{z}, \overline{z}]$. It follows that not the full range of the interval $z \in [\underline{z}, \overline{z}]$ have to be continuously one type of equilibrium. If (11) holds, i.e. $z \in [\underline{z}, \overline{z}]$, there exist some values for y and a that $\underline{z}$ is a partial non-degenerate equilibrium and $\overline{z}$ a perfect non-degenerate equilibrium. Consequently, there exist a value $z = 1 - a(1-y)$ where both high and low skilled experts' condition for adaptation hold.

□

Expert's reaction function, i.e. their probability of choosing high effort in non-degenerate equilibria, according to f is given by

[3] Notice that we leave out condition $z \leq 1$ for high skilled expert adaptation, as it is always fulfilled.

$$x_e(f) = \begin{cases} x_t = 0 & \text{if } f > f_t^* \\ x_t \in \{\underline{x_t^*}, \overline{x_t^*}\} & \text{if } f = f_t^* \neq 0 \\ x_t \in [\underline{x_t^*}, \overline{x_t^*}] & \text{if } f = f_t^* = 0 \\ x_t = 1 & \text{if } f < f_t^* \end{cases} \tag{20}$$

We return to the influence of a and y, as well as which equilibria type will be preferred by experts or consumers in the welfare section section.

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), if $N \geq \frac{2}{z}$, $s+d < \bar{s} = V(3-2\sqrt{2})$, and $V - p - 2\frac{s+d}{z} > 0$: (i) With $2c \leq p$, consumers will choose $f = f_l^*$, if (17) and (18) are holding, resulting in a partial non-degenerate equilibrium. 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 (19) holds, consumers will choose $f = f_h^*$, resulting in a perfect non-degenerate equilibrium. 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 always choose $x_l = 1$.*

Proof of Lemma 4: See Appendix A.

□

As outlined by the proof of Lemma 4, the feasibility of non-degenerate equilibria types depends not only on market composition, outlined by the adaptation conditions, but also on parameter values, i.e. the ratio of service price and high effort costs in combination with high skilled experts' degree of qualification. With an increasing markup for service, a perfect non-degenerate equilibrium becomes possible. However, with experts always need to adapt their effort choices according to market composition to keep consumers indifferent, in any equilibrium the possible interval for z remains constant in high skilled, as well as in low skilled equilibria and only changes, if V, d and s, change.

3.2 Equilibria with Flexible Prices

In the next step, we turn to equilibria under flexible prices. Experts now have the possibility to choose their contracts (d_t, p_t) individually. For being an equilibrium, it is necessary that all experts choose a strategy profile $(d_t, p_t, \varepsilon_t)$, conditional on their consistent belief B, and consumers adapt a corresponding searching behavior, described by f.

As before, there is always the possibility for degenerate equilibria, if the defined market conditions are not fulfilled. In this case, consumers will not enter the market unless $ay > \frac{2(s+d)}{V-p}$.

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, i.e. $N \geq \frac{2}{z}$, and $V-p-2\frac{s+d}{z} > 0$. 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 $f = f^*(q_t) = 1 - \frac{2c}{p(1-q_t y)}/1 + \frac{c(z-2)}{p(1-q_t y)}$. According to 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 $p \in [2c, V-\frac{2c}{z}]$. (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: Our proof of Lemma 5 is based on Pesendorfer, Wolinsky (2003) and adapted for our case with heterogeneous experts. However, while we do not replicate every single calculation in the beginning, the interested reader can find it there. Again, an equilibrium in pure strategies is not feasible due to the formerly stated reasons. In order to enable a mixed strategy equilibrium, consumers need to choose $f \in]0,1[$. Consequently, (11) needs to hold with equality, which requires $z \in \{\underline{z},\bar{z}\}$.
With the introduction of heterogeneous experts, there might be the possibility for experts to signal their type by different price setting behavior. This could potentially lead to different equilibrium strategies according to individual qualification, resulting in different prices for diagnoses or services. However, there will not be competition in diagnosis fee d. There is no incentive for experts in trying to signal higher qualification by higher prices in diagnosis, as consumers are not able to verify skill neither ex ante nor ex post. According to 10, experts' effort decision is independent of d. Low skilled experts, therefore, could always mirror higher diagnosis prices and cannot be driven to always provide wrong diagnoses, i.e. $x_l = 0$. Using a standard Bertrand argumentation, d must be zero for all experts because from the moment on a consumer agrees to being diagnosed, these costs are sunk and non-binding for experts investment decision, irrespective of their skill. Accordingly, d has no effect on experts' effort choice. If $d > 0$, experts' would be able to accumulate full market demand on their own by setting $d' < d$, since consumers are unable to differentiate. Therefore, the only feasible equilibrium outcome with flexible prices is $d = 0$.

In contrast to the diagnosis fee, the price for service directly affects experts' effort choices. However, there is no incentive for any expert to increase a given price p. Recall that

$$d + fBp + (1-fB)\frac{p}{2} - c \geq d + fBp + qp(1-fB)\frac{y}{2}$$

is necessary in order to attract an expert for high effort. If he increases his price to $p' > p$, he will loose all consumers who are looking for matching opinions, as they could buy the same service cheaper elsewhere. Consequently, there is no incentive for experts of any kind to increase their price above an established equilibrium level. However, there might be an incentive to undercut prices for accumulating full demand from consumers who are looking for matching opinions. For an expert to deviate from a given situation $(d = 0, p, z, f)$, two conditions need to be fulfilled: it needs to be profitable for the deviating expert and consumers need to prefer the deviating offer (d', p') as well.

Let a consumer's difference in expected continuation value for contacting the deviating expert be given by

$$\Delta(d', p'; 0, p, z) = \left(\frac{s}{z} + p - p'\right) \frac{V - 2(s/z) + p' - p}{V - (s/z) + p' - p} - s - d'. \tag{21}$$

For being an equilibrium, consumers must not have an incentive for accepting the deviating offer. As outlined before, a price deviation with $p' > p$ is not feasible, as experts would always choose low effort which makes it unattractive for consumers to follow. However, it might be profitable for a consumer to follow a price reduction with $p' < p$. This depends on whether the price reduction (over-)compensates a deviating expert's reduction in high effort. Assuming that p' is arbitrarily close to p, we receive

$$\frac{\partial}{\partial p'} \Delta(d', p'; 0, p, z | p' = p) = -1 + \frac{Vs}{z(V - \frac{s}{z})^2}. \tag{22}$$

From (22) follows that $\frac{\partial}{\partial p'} \Delta(d', p'; 0, p, z | p' = p) \geq 0$ if $z \in [\frac{s(3-\sqrt{5})}{2V}, \frac{s(3+\sqrt{5})}{2V}]$. If z does not lie within this interval, consumers would strictly prefer a price $p' < p$.

According to the equality of (11), z can only take the two roots of the determined interval. As there is no possibility for $\bar{z}$ to lie within $z \in [\frac{s(3-\sqrt{5})}{2V}, \frac{s(3+\sqrt{5})}{2V}]$, only $\underline{z}$ might be a flexible price equilibrium.[4] Consequently, it requires that

$$s(3 - \sqrt{5}) \leq V + s - \sqrt{(V + s)^2 - 8sV} \leq s(3 + \sqrt{5}). \tag{23}$$

Solving (23) gives the possible range for the transaction costs $s \in [0, \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}]$.[5] In sum, given the profile $(d = 0, p, \underline{z}, f)$, with $s \leq \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}$, there is no incentive for consumers to follow a deviating expert who offers $p' < p$. With consumers restrain from following a price reduction, there is no incentive for experts to choose $p' \neq p$.[6]

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

[5]Notice that the lower bound for z resulting from (22), is fulfilled if $s = 0$ or $s \leq \frac{V(2+2\sqrt{5})}{4\sqrt{5}-8}$. Since $\frac{V(2+2\sqrt{5})}{4\sqrt{5}-8} > \bar{s} = V(3 - 2\sqrt{2})$, this is fulfilled in every non-degenerate equilibrium.

[6]Notice that according to (22) with $z \in]\frac{s(3-\sqrt{5})}{2V}, \frac{s(3+\sqrt{5})}{2V}[$, consumers would prefer $p' > p$. However, since

The minimum price for an equilibrium is $p = 2c/(1-q_t y)$. According to (10), experts would strictly prefer low effort, if it falls below which would make consumers to stay away from the market from the beginning. The maximum price for an equilibrium is $p = V - 2s/z$ which represents the total surplus for consumers who are searching for matching recommendations. In sum, if there would be only low skilled experts in the market, i.e. $a = 0$, any price within $p \in [2c, V - \frac{2c}{z}]$ could be an equilibrium, depending on the formerly defined conditions.

In a given equilibrium with both high skilled and low skilled experts choosing $x_t > 0$, low skilled experts might have an incentive fur undercutting an existing price level to accumulate full demand of consumers who are searching for matching opinions on their own. Imagine there is an established price $p = \frac{2c}{(1-y)}$. For high skilled experts, there is no possibility to reduce this price any further while credibly committing to $x_h > 0$. In contrast, low skilled experts could undercut this price level while still choosing $x_l > 0$. With $p' < \frac{2c}{(1-y)}$, they would force high skilled experts to follow the price reduction and, as a consequence, to always choose low effort which would make them lose all consumers searching for matching opinions. Notice that in case high skilled experts would not follow the price reduction, they are clearly distinguishable from low skilled experts with the consequence of being abandoned altogether, since in this case $x_h = 0$. The only possibility for getting a positive expected payoff would be to follow the price reduction.

However, as long as conditions (17) and (18) hold, consumers anticipate experts' adaptation behavior and choose the partial non-degenerate equilibrium strategy from the beginning, i.e. $f = f_l^*$. This implies that the full price range $p \in [2c, V - \frac{2c}{z}]$ is feasible and there is no possibility for a perfect non-degenerate equilibrium. According to (22), low skilled experts will never undercut a given price within this interval, as long as $s \in [0, \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}]$, and will choose $x_l = \underline{x_l^*} = (\underline{z} - ay)/(1-a)$.

If (17) no longer holds, low skilled consumers are no longer able to balance $x_h = 0$. Consequently, a partial non-degenerate equilibrium becomes impossible. With $V - p - 2\frac{s+d}{z} > 0$, consumers strictly prefer a perfect non-degenerate equilibrium. As high skilled experts will always choose low effort if $p < \frac{2c}{1-y}$, the possible price range for equilibrium reduces to $p \in [\frac{2c}{1-y}, V - \frac{2c}{z}]$. Again, experts do not have an incentive to undercut a given price as long as (22) holds and $s \in [0, \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}]$, since consumers would not follow a deviation.

□

Notice that different price levels are compatible with equilibrium due to consumers' adaptation of their search behavior f. As outlined by Pesendorfer, Wolinsky (2003), higher price levels,

we assume services being perfect substitutes, consumers are always buying the service with the cheapest price and, therefore, would buy at p. This implies that with $p' > p$ an expert would loose all consumers searching for matching opinions. Consequently, there is no incentive for experts to offer higher prices.

which are associated by increased incentives for high effort must be counterbalanced in equilibrium by lower rates of searching for matching opinions.

3.3 Welfare

In this section, we will analyze welfare implications, depending on formerly determined equilibria. We will focus on the influence of market composition, i.e. the share a of high skilled experts in the market and their degree y of qualification, how this influences the possibility for welfare maximization and its determinants.
The present model does not allow for Pareto optimality. Since search is costly with all transaction costs being lost, optimality would require consumers to stop and to buy after one recommendation, as well as experts always choosing high effort. As this is not incentive compatible by also the introduction of high qualified experts in the market, there is no possibility for a first best outcome. Instead, we will focus on potential second best outcomes. We define an equilibrium (d,p,z,f) as second best, if it maximizes overall welfare under fixed market composition, i.e. a, y and the proportion of consumers in the market $k = M/(M+N)$, as well as under fixed market conditions, i.e. c, s and V, in comparison to any other equilibrium (d',p',z',f'). Consequently, we assume that only d, p, z and f are endogenous.
In the following, we first analyze consumer and expert welfare separately and how it can be maximized for certain groups. Afterwards, we show how overall welfare would be maximized, given market conditions and composition.

Consumer Welfare
In any non-degenerate equilibrium with the profile (d,p,z,f), consumer welfare is given by

$$\pi_c(f,z) = f(zV - p - (s+d)) + (1-f)(V - p - \frac{2(s+d)}{z}), \tag{24}$$

with $f = f^*(q_t) = 1 - \frac{2c}{p(1-q_t y)}/1 + \frac{c(z-2)}{p(1-q_t y)}$ and $z = ax_h + (1-a)x_l + (1-x_h)ay \in [\underline{z},\bar{z}]$. As long as $z \in \{\underline{z},\bar{z}\}$ and $p < V - 2(s+d)/z$, consumers are indifferent between any kind of non-degenerate equilibrium, since (11) holds with equality. Consequently, depending on the ratio of service price p, costs for high effort c and high skilled expert qualification y, there is no effect of either y or a on consumer welfare. Notice that this result is independent of the defined adaptation conditions. As this payoff represents the minimum payoff for consumers in equilibrium to participate in a given market, we determine it as $\underline{\pi_c}$.
For consumers to realize a higher expected payoff than $\underline{\pi_c}$, two conditions, among market conditions for non-degenerate equilibria, need to be fulfilled: (11) needs to hold with strict inequality enable $z \in]\underline{z},\bar{z}[$, and depending on the price ratio for service p, the adaptation conditions must hold.

As we have outlined in the former section that only $z = \underline{z}$ can be a non-degenerate flexible price equilibrium, there is no possibility for consumers to realize a higher than their minimum payoff with flexible prices.

Assuming fixed prices, there is the possibility for $\pi_c > \underline{\pi_c}$ in scenario (*ii*) and scenario (*iv*). In scenario (*ii*) $p = 2c$. Assuming adaptation conditions (17) and (18) hold, low skilled experts are able to balance $x_h = 0$. Moreover, with $p = 2c$, low skilled experts are indifferent between any value for x_l within $[\underline{x_l^*}, \overline{x_l^*}]$, since they get an expected payoff of zero, which enables (11) to hold with strict inequality, if $z \in]\underline{z}, \bar{z}[$. As a consequence, consumers will opt for $f_l^* = 0$ which leads to $\pi_c^l > \underline{\pi_c}$, since $\partial \pi_c / \partial f < 0$.

A similar argumentation holds for scenario (*iv*), $p = \frac{2c}{1-y}$. Assuming $a > \frac{1-z}{1-y}$, high skilled experts can balance $x_l = 1$ and the price level is high enough to attract them for $x_h > 0$. Moreover, with $p = \frac{2c}{1-y}$, high skilled experts are indifferent between any value for x_h within $[\underline{x_h^*}, \overline{x_h^*}]$, since they get an expected payoff of zero, which enables (11) again to hold with strict inequality. As a consequence, consumers will opt for $f_h^* = 0$ instead of $f_l^* > 0$, since $\partial \pi_c / \partial f < 0$, implying $\pi_c^h > \underline{\pi_c}$.

In sum, assuming a benevolent policy maker, consumers payoff can be increased by setting prices according to market composition, i.e. the share of high skilled experts a and their degree of qualification y. This can increase consumer welfare to $\pi_c^l, \pi_c^h > \underline{\pi_c}$. Since $\partial \pi_c / \partial p < 0$, consumer welfare is maximized with $p = 2c/(1 - q_t y)$.

Expert Welfare

With all experts offering identical contracts (d, p), the probability for an expert for being visited by a single consumer depends on the total number of experts and consumers in the market and is given by its ratio M/N. Moreover, notice that the formerly used expert payoffs, i.e. (6) and (7), were conditional on a consumer accepting his contract. Since consumers accept on average S_t contracts, each experts is expected to get consulted for $(M/N)S_t$ times, receiving the diagnosis fee d and bearing the potential costs for high effort $x_t c$ every time. Consequently, in any non-degenerate equilibrium with the profile (d, p, z, f), individual expert welfare depending on qualification q_t is given by

$$\pi_e(x_t, q_t, f) = \frac{M}{N}[S_t(d - x_t c) + fBp + (1 - fB)\frac{p}{2}(x_t(1 - q_t y) + y)], \tag{25}$$

with $fB = f^*(q_t)B = 1/(1 + \frac{2c}{p(1-q_t y)-2c})$, $S_t = f^*(q_t) + 2(1 - f^*(q_t))/z$, N as the total number of experts and M as the total number of consumers in the market. Since $\partial \pi_e / \partial p > 0$, experts welfare strictly increases in p, irrespective of individual qualification. Moreover, with $d > c$, expert welfare strictly increases ceteris paribus with consumers consulting more experts on average, i.e. with an increasing S_t.

Assume a situation with $a(1-y) \leq 1-z$ and $ay \leq z$, consumers will choose $f = f_l^*$, resulting in $x_l = x_l^*$ and $x_h = 0$, if $p \geq 2c$. In this situation, a low skilled expert gets an expected payoff of

$$\pi_e^l(x_l^*, f_l^*) = \frac{M}{N}[S_l(d - x_l^* c) + f_l^* Bp + x_l^*(1 - f_l^* B)\frac{p}{2}]. \tag{26}$$

In contrast, a high skilled expert's expected payoff amounts to

$$\pi_e^h(x_h = 0, f_l^*) = \frac{M}{N}[S_l d + f_l^* Bp + (1 - f_l^* B)\frac{py}{2}]. \tag{27}$$

If low skilled adaptation fails and only high skilled experts are able to adapt with $a(1-y) > 1-z$ with $p' \geq \frac{2c}{1-y}$, consumers will choose $f = f_h^*$, resulting in $x_h = x_h^*$ and $x_l = 1$. Now, low skilled experts gain an expected payoff of

$$\pi_e^l(x_l = 1, f_h^*) = \frac{M}{N}[S_h(d - c) + f_h^* Bp' + (1 - f_h^* B)\frac{p'}{2}]. \tag{28}$$

In contrast, high skilled expert expected payoff amounts to

$$\pi_e^h(x_h^*, f_h^*) = \frac{M}{N}[S_h(d - x_h^* c) + f_h^* Bp' + (1 - f_h^* B)\frac{p'y + p'x_h^*(1-y)}{2}). \tag{29}$$

In building the difference, we can analyze which equilibrium gain the higher expected payoff for experts by assuming identical contracts $(d, p = p')$. With $f^*(q_t)B = 1/(1 + \frac{2c}{p(1-q_t y) - 2c})$ we get a difference for low skilled experts, given by

$$\Delta\pi_e^l = \frac{M}{N}[\Delta S(d - (1 - x_l^*)c) - cx_l^* + c\frac{1-2y}{1-y}], \tag{30}$$

with $\Delta S = S_h - S_l$. Whether low skilled experts gain in terms of welfare by a switch to the high skilled equilibrium depends primarily on the ratio of d and c, as well as on the absolute value of y. Since $\Delta S > 0$ as long as $y > 0$, low skilled expert welfare strictly increases by an equilibrium switch, as long as $d > c$ and $y < 0.5$. Under these circumstances, this increase stems from additional gains by higher income from diagnosis fees and a higher probability for selling services to consumers searching for matching recommendations, outperforming the increase in high effort costs and the decrease in selling services to consumers being on their first visit. With $d > c$, low skilled consumers are strictly worse off by an increase in y, since $\partial \Delta S / \partial y < 0$ and the fraction of the equation also decreases in y.

In contrast, the difference for a high skilled expert is given by

$$\Delta\pi_e^h = \frac{M}{N}[\Delta S d - cx_h^*(S_h - 1) - \frac{2cy}{1-y}(1 - \frac{y}{2})]. \tag{31}$$

Whether high skilled experts gain in welfare by a switch to the high skilled equilibrium is also primarily determined by the ratio of d and c and the absolute value of y. It is quite surprising that they strictly lose welfare by an increasing degree of qualification, since both ΔS and the last term of the equation decreases in y. It can be easily seen that the additional gains due to their higher qualification y happen in both kind of equilibria with $(1-f^*(q)B)p/2$. However, with increasing y the term $(1-f_h^*)px_h^*(1-y)/2$ decreases which implies a reduction for high skilled experts in the high skilled equilibrium. Consequently, with d being relatively low and high skilled experts are well qualified, i.e. with y being relatively high, high skilled experts prefer the low skilled equilibrium.

Overall Welfare

In former sections, we have outlined how the separate welfare of consumers and experts are affected by various factors and whether they gain or lose by a switch to the high skilled equilibrium. Since, so far, it remains questionable how societies welfare can be maximized in our setting and whether an equilibrium switch would be worthwhile, we analyze how overall welfare reacts to changes in the setting. We assume that there is a share $k = \frac{M}{M+N}$ of consumers and a share $1-k = \frac{N}{M+N}$ of experts in the market. Therefore, overall welfare, as a combination of consumer and expert welfare, is given by

$$\pi = k[f(zV-p-(s+d)) + (1-f)(V-p-\frac{2(s+d)}{z})] \tag{32}$$

$$+(1-k)\frac{M}{N}[S_e(d-c(ax_h+(1-a)x_l)+fBp+\frac{2}{z}(1-fB)\frac{pz}{2}]. \tag{33}$$

The first line of the equation is determined by consumer welfare. Its relative influence is given by the share of consumers in the market k. The second line is given by expert welfare. However, notice that expert welfare is directly determined by how many experts are consulted by consumers, which is displayed by the term M/N. As outlined in the section for expert welfare, each consumers consults on average S_t experts for a recommendation. Moreover, from Lemma 1 follows that each consumer will buy exactly one service in case she enters the market. Consequently, each experts sells on average M/N services with the individual probability depending on f, x_t and y. Since in case a consumer searches for matching opinions, she will visit in sum $2/z$ experts who have on average the probability $(1-fB)z/2$ for selling a service.

In equilibrium, $f = f^*(q_t)$, $fB = f^*(q)B = 1/(1+\frac{2c}{p(1-qy)-2c})$ and $ax_h + (1-a)x_l + (1-x_h)ay = z \in \{\underline{z}, \overline{z}\}$. Moreover, note that $(1-k)MS_t/N = kS_t$ and $S_t = f^*(q_t) + (1-f^*(q_t))2/z$. Accordingly, we receive the following equilibrium outcome for overall welfare

$$\pi(f^*, z, a, y, k) = k[f_q^*(zV - s - c(z - (1-x_h)ay) \tag{34}$$

$$+ (1-f_q^*)(V - \frac{2s}{z} - 2c + \frac{2c}{z}(1-x_h)ay)]. \tag{35}$$

Overall welfare in equilibrium depends on the endogenous factors z and $f^*(q_t)$, which are determined in equilibrium by offered contracts (d, p), as well as by market composition, i.e. k, a and y. While the former variables are influenced within a given equilibrium, the market composition factors are assumed to be external and only amendable in the long run.
We investigate how the possible range for z is determined in equilibrium and how it affects overall welfare. In every non-degenerate equilibrium, z is determined by the values of V, d and s only. In contrast to the transaction costs s and the valuation for consumers of a solved problem V which directly affect overall welfare, d is welfare neutral but affects whether experts will become better off by a change to a high skilled equilibrium. However, with decreasing d, the possible range for $z \in [\underline{z}, \overline{z}]$ increases. Consequently, when overall welfare should be maximized, independently whether z has a positive or negative effect, d needs to be minimized.
We now analyze how z affects overall welfare. Since in all non-degenerate equilibrium with $f^*(q_t) > 0$, z which will be determined only by market conditions, i.e. d, V and s. Consequently, in this cases, we can treat z as being independent in equilibrium from x_h and x_l. By building the f.o.c. we get

$$\frac{\partial \pi}{\partial z} = k[f_q^*(V-c) + 2(1-f_q^*)(\frac{s - c(1-x_h)ay}{z^2}). \tag{36}$$

By inserting $f = f^*(q_t) = (p(1-q_t y) - 2c)/(p(1-q_t y) + (z-2)c)$ and solving for p, we receive

$$p > p^* = \frac{2c + \frac{c(2c(1-x_h)ay - 2s)}{z(V-c)}}{1 - q_t y}. \tag{37}$$

Notice that in a market with only few and/or relatively lowly qualified high skilled experts, i.e. with $ay < s/c(1-x_h)$, (37) always holds, since $p \geq 2c/(1-q_t y)$.
However, independently of whether an increase in z increases or decreases overall welfare, the only choice for d, in order to maximize welfare, is given by $z(d=0)$, since a decrease in d strictly widens the interval for z in any non-degenerate equilibrium. Depending on market composition, either $\underline{z}(0)$ or $\overline{z}(0)$ will maximize overall welfare.

In the next step, we now turn to the optimal value for f_q^*. In every non-degenerate equilibrium, the possible values for $f^*(q_t)$ are determined by p, c, y and z. We have already shown that in all welfare maximizing states $z \in [\underline{z}(0), \overline{z}(0)]$. This implies that (11) needs to hold with equality. Since $d = 0$, we get

$$zV - p - s = V - p - \frac{2s}{z}. \tag{38}$$

By using (34) and (38), we get the following inequality equation as condition for $\partial\pi/\partial f > 0$

$$-c(z - (1 - x_h)ay) > -2c(1 - \frac{(1 - x_h)ay}{z}). \tag{39}$$

Solving for ay gives

$$ay < \frac{z}{1 - x_h}. \tag{40}$$

This corresponds to the second adaptation condition for low skilled equilibria. Consequently, as long as $ay < z$, which is given in all non-degenerate low skilled equilibria, there is $\partial\pi/\partial f > 0$. However, if the relative amount of high skilled experts, as well as their qualification increases above the defined threshold, this relationship turns to $\partial\pi/\partial f < 0$ but cannot be a low skilled equilibrium anymore.

According to Lemma 3, in a non-degenerate equilibrium the probability for consumers to stop and purchase after their first recommendation $f^*(q_t)$ is given by (14) which increases strictly in p. Consequently, in every welfare maximizing equilibrium, p needs to be either $\underline{p} = 2c/(1 - qy)$ or $\overline{p} = zV - (d + s)$ in order to maximize or minimize $f^*(q_t)$. With an increasing price in service, it becomes more attractive for experts to invest high effort which, furthermore, increases consumers' tendency to stop after their first visit.

According to (40), in every low skilled welfare maximizing equilibrium, it is necessary that $\overline{p} = zV - (d + s)$ and $d = 0$, which results in

$$\overline{f_l^*} = \frac{z(0)V - s - 2c}{z(0)V - s + c(z(0) - 2)}. \tag{41}$$

In a corresponding high skilled equilibrium, we receive either $\underline{p} = 2c/(1 - qy)$ with $\underline{f_h^*} = 0$ or $\overline{p} = zV - (d + s)$ with

$$\overline{f_h^*} = \frac{(1 - y)(z(0)V - s) - 2c}{(1 - y)(z(0)V - s) + c(z(0) - 2)}. \tag{42}$$

Proposition 1: *If (d, p, z, f) is second best, then $z \in \{\underline{z}, \overline{z}\}$ and $d = 0$. According to market composition, there are the following possible second best equilibria (SBE):*

(i) *if $p > p^*$, $a(1 - y) \leq 1 - z$ and $ay < z$, $(0, \overline{p}, \overline{z}(0), \overline{f_l^*})$;*

(ii) *if $p > p^*$, $ay < z/(1 - x_h^*)$ and $a(1 - y) \geq 1 - z$, $(0, \overline{p}, \overline{z}(0), \overline{f_h^*})$;*

(iii) *if* $p < p^*$, $ay > z/(1-x_h^*)$ *and* $a(1-y) \geq 1-z$, $(0, \underline{p}, \underline{z}(0), \underline{f_h^*})$.

Proof of Proposition 1: See Appendix C.

SBE (i) is feasible with adaptation conditions for a low skilled equilibrium holding, while SBE (ii) and (iii) correspond to high skilled equilibria. Whether and which SBE is actually feasible will be determined by market composition, as well as market conditions. For a social planer to maximize welfare by intervention, for example by stipulating some price level for services, it is essential to know about the market. As long as such a social planer is assumed to be only able to determine price levels for diagnosis d and service p, to maximize welfare she needs to apply to the outlined SBE conditions. Notice that according to the dependence of p^*, which determines the optimal level for z in any SBE, on z itself, there is the possibility that a given market can reach two different kinds of SBE, with either $\underline{z}$ or $\overline{z}$. In the next step, we investigate whether the outlined SBEs are stable.
According to Pesendorfer, Wolinsky (2003), in any given equilibrium (d, p, z, f) with $p > p^*$, the level $\overline{z}$ for consumers to receive a correct diagnosis cannot hold with flexible prices, since experts have an incentive to deviate to a lower price or reduce their effort level. Assuming a service price $p = 2c/(1-y)$, with flexible prices, z must get reduced to prevent price undercutting and cannot be second best. We do not replicate their full discussion, as the interested reader can find it there. However, they conclude due to this reduction in effort levels in a non-degenerate flexible price equilibrium, that price regulation might be beneficial in order to achieve SBE (i).
In a market with only low skilled experts, i.e. $a, y = 0$, there is only one potential SBE. As we introduced high skilled experts in the model, the variety for possible SBE increases to three. Nevertheless, the argumentation of Pesendorfer, Wolinsky (2003) regarding the instability of any flexible price equilibrium with $p > p^*$ and $\overline{z}$ still holds. Consequently, only SBE (iii) might be stable in this case.
In any SBE $d = 0$ and, therefore, s needs to be relatively large in SBE (iii), as otherwise $\underline{z}$ becomes close to zero which would make the possibility for a high skilled equilibrium, i.e. $f = f_h^*$ with $x_h = x_h^*$ and $x_l = 1$, more improbable. We have outlined that in any non-degenerate equilibrium with flexible prices, $s \in [0, \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}]$. In contrast, with fixed prices, $s \leq V(3-2\sqrt{2}) > \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}$. This implies that a market with flexible prices, needs a greater share a of high skilled experts for being an equilibrium with $(0, \underline{p}, \underline{z}(0), \underline{f_h^*})$, as otherwise an adaptation of high skilled experts is not possible. Moreover, since $\underline{z}$ is relatively small, the condition regarding the necessary number of experts in the market to enable an equilibrium $N > 2/z$ increases. Consequently, SBE (iii) is only feasible in markets with relatively large transaction costs and a relatively large number of contactable experts.

In SBE (iii) p equals the minimum price $\underline{p} = 2c/(1-y)$ for a non-degenerate high skilled equilibrium. This implies that experts will make zero profits and all generated welfare is shifted to consumers. Moreover, $f = f_h^* = 0$ implies that consumers will always search for matching opinions. Referring to Pesendorfer, Wolinsky (2003), this small probability $\underline{z}$ results in high costs to verify an expert's recommendation. This makes it less attractive for consumers to accept an expert's offer who deviates from equilibrium price. As we have outlined in 3.2, with $z = \underline{z}$ and $s \leq \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}$, a non-degenerate equilibrium is possible which also would be second best to our definition. However, notice that from (19) follows that in markets with relatively low transaction costs, the possibility for a stable SBE becomes the more improbable the more $\underline{z}$ approaches to zero and the higher qualified high skilled experts are.

4 Conclusion

Even though there is a broad literature on credence goods markets, analysis with experts having to invest in costly diagnosis to identify consumers' problems are rare. In such markets, consumers are neither able to observe effort decisions nor whether an expert is high or low skilled, which results in a moral hazard problem. Instead of assuming a homogeneous level of qualification, in reality there are considerable differences in skills among experts of any given field. While Pesendorfer, Wolinsky (2003) assume low skilled experts to always deliver an incorrect diagnosis, we argued that this will depend on their willingness to invest effort in their diagnosis. High skilled experts' advantage, therefore, only consists in being able to carry out diagnosis with less effort but not having monopoly power for correct diagnosis. For this reason, we introduce heterogeneous experts into the model of Pesendorfer, Wolinsky (2003) where consumers can visit multiple experts to verify recommendations. For simplification, we assume experts being either high or low skilled. We model this by high skilled experts having some probability to identify consumer problems even with low effort while low skilled experts always give a false recommendation in this case.
Our results show that second best equilibria are possible in the presence of high skilled experts, even with flexible prices. However, for such an equilibrium being stable requires special market circumstances, whereby transaction costs for consumers must lie under a specific threshold. Additionally, the share of high skilled experts needs to be relatively large and their edge in qualification relatively low. If these conditions are not fulfilled, it might be worthwhile for policy-makers to intervene by fixing service prices to increase overall welfare. According to our results, there might be an incentive for policy makers to regulate service prices in markets with only few or rather extremely heterogeneously qualified experts. However, if one drops the assumption that market composition cannot be influenced externally, there can be an incentive to regulate the share of high skilled experts. As not only the possibility of

SBEs but of any non-degenerate equilibrium in general depends on consumers' transactions costs not exceeding the given threshold, market breakdowns might be prevented by reducing consumers' costs for visiting an expert. However, in any second best equilibrium, all welfare surplus is either accumulated completely with consumers or with experts, which might make welfare maximization complicated.

Even though our model incorporates many dimension regarding market conditions and market composition, it has some open space for further research. Our assumption that there is always only one service which yields consumers a positive payoff is quite strict. It appears much more realistic that consumers value undertreatment and overtreatment differently, as the latter actually solves their problem. However, while this would make the model more complicated, it would not change its form in general (Pesendorfer, Wolinsky, 2003). Moreover, in a next step, it would be interesting to drop the assumption that market composition cannot be influenced externally. While this would be accompanied by introducing some costs for qualifying experts, it might be worth this investment with regard to the potential gains in overall welfare by enabling a SBE.

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Appendix A - Proof of Lemmas

Proof of Lemma 1:
Since $s+d>0$, receiving recommendation(s) without purchase cannot be optimal for a consumer. This implies, to enter the market she must get a positive expected utility from purchasing, which is only possible with buying a service based on a correct diagnosis. Moreover, it cannot be optimal for consumers to continue searching after having received two matching recommendations, since searching is costly and matching recommendations reveal a correct diagnosis.[7]
By adapting the proof of Pesendorfer, Wolinsky (2003), we show that stopping and purchasing after two or more non-matching recommendations cannot be optimal.

Suppose a consumer has contacted $2 \leq n < N$ experts who gave all different recommendations. Let $\phi(n)$ be the probability that exactly one randomly drawn recommendation out of these n resembles the correct diagnosis.

$$\phi(n) = \frac{(1-z)^{n-1}z}{(1-z)^n + n(1-z)^{n-1}z} = \frac{z}{1+(n-1)z}.$$

Let $\tau(n)$ be the probability that the next recommendation, i.e. the (n+1)-st, will match one of the former n recommendations.

$$\tau(n) = nz\frac{z}{1+(n-1)z}.$$

While still assuming this consumer has contacted n experts who gave distinct recommendations, to continue searching for matching opinions she needs her expected continuation value W^n to be at least equal her outside option, i.e. $W^n \geq -\sum_{j=1}^{n} d_j - ns$. Since she can always decide to buy from the last contacted expert, continuation in searching also requires

$$W^n \geq zV - p - (s+d),$$

For being a best response, a consumer needs to maximize W^n. This maximization problem stems from consumers always having the choice to (i) leave the market without purchase; (ii) buy a service based on any former recommendation; (iii) get a new recommendation if $n < N$. Consequently, assuming $n < N$, consumers face the following maximization problem

$$max(W^n) = max\{-\sum_{j=1}^{n} d_j - ns, \phi(n)V - p, -(s+d) + (1-\tau(n))W^{n+1} + \tau(n)(V-p)\},$$

As consumers' outside option shrinks by the number of contacted experts, it decreases in n. Consequently, if a consumer's expected profit by entering the market is positive with $n=0$ contacted experts, it could never be optimal to leave the market for the outside option after $n>0$ consulted experts.
If a consumer decides for getting another recommendation, she will receive matching ones with probability $\tau(n)$ and will buy the service from one of the two experts. With probability $1-\tau(n)$ she gets another recommendation.

[7] Due to extreme improbability of matching wrong signals we exclude this case from analysis.

Assuming it would be optimal if she buys the service in $n+1$ while still having different recommendations only, her expected utility would be

$$W^{n+1} = \phi(n+1)V - p.$$

Inserting this into the former maximization problem gives

$$\begin{aligned} max(W^n) &= max\{-\sum_{i=1}^{n} d_i - ns, \phi(n)V - p, -(s+d) + (1-\tau(n))(\phi(n+1)V - p) + \tau(n)(V-p)\} \\ &= max\{-\sum_{i=1}^{n} d_i - ns, \phi(n)V - p, -(s+d) + Vz - p\} \end{aligned}$$

According to the assumption $\phi(n+1)V - p = W^{n+1} \geq max\{-\sum_{i=1}^{n} d_i - ns, -(s+d) + Vz - p\}$. Since $\phi(n)$ is decreasing in n, we get

$$\phi(n)V - p > max\{-\sum_{i=1}^{n} d_i - ns, -(s+d) + Vz - p\}.$$

This reveals that it would be optimal to buy after n distinct recommendations instead after $n+1$. Consequently, it could never be optimal for a consumer to purchase after two or more different recommendations.
In contrast to Pesendorfer, Wolinsky (2003), we introduced a limited number of N experts in the market. This might change consumers' behavior as they are no longer able to search infinitely long for matching recommendations. If a consumer has consulted $n = N$ experts and received distinct recommendation only, she is not able to continue searching for matching opinions. In this case, she has to decide whether to purchase a service from any formerly visited expert or leave the market without purchase. In this case, a consumer's maximization problem becomes

$$max(W^{n=N}) = max\{-\sum_{i=1}^{N} d_i - ns, \phi(n)V - p\}$$

Setting outcomes equal, we receive a critical threshold for z, given by

$$z^* = \frac{p - n(s+d)}{V - (n-1)[p - n(s+d)]}.$$

In maximizing her welfare, a consumer will opt for purchasing from a random expert if $n = N$ and $z > z^*$. Otherwise she will choose to leave the market without purchase. However, ending up with $n = N$ distinct recommendations cannot be optimal, as not only the outside option decreases in n but it would have been better to purchase the service from any of the $n-1$ consulted expert before as well. Consequently, ending up with $n = N$ non-matching recommendations cannot be an equilibrium. A consumer will only opt to search for matching opinions if its expected duration $\frac{2}{z}$ does not exceed the available number of N experts in the market.

In sum, if consumers decide to enter the market, they will...

- never leave the market without purchase if $n < N$;

- never stop and buy after receiving different recommendations only, if $n < N$ or $z < z_{crit}$;
- either stop after the first recommendation with purchasing;
- or search until two recommendation coincide and then purchase;
- will leave without purchasing, if they have received $n = N$ distinct recommendations and $z < z^* = \frac{p-n(s+d)}{V-(n-1)[p-n(s+d)]}$.

Proof of Lemma 4:

As outlined before, feasibility of non-degenerate equilibria and their kind depend on parameter values p, c, a and y. We, therefore, have to define the following scenarios where we assume that the market conditions for non-degenerate equilibria are fulfilled.

(i) *Scenario (i)*

$$p < 2c \rightarrow \{ \; x_h, x_l = 0$$

In scenario (i), there is no possibility for a non-degenerate equilibrium of any kind, since the fixed price for service is too low in comparison to high effort costs. Even if consumers are searching for matching opinions all the time, they cannot make any kind of experts willing to choose high effort, since (10) is not fulfilled. Consequently, there will be a degenerate fixed price equilibrium in which all experts would always choose low effort and consumers do not enter the market. However, if there is a substantial high share of very well qualified experts in the market, consumers are willing to enter the market by searching for matching opinions, i.e. if $ay > \frac{2(s+d)}{V-p}$. This does not change experts effort choice, though.

(ii) *Scenario (ii)*

$$2c = p < 2c/(1-y) \rightarrow \begin{cases} x_l \in [\underline{x_l^*}, \overline{x_l^*}], x_h = 0 & \text{if } f = f_l^* = 0 > f_h^* \\ x_h, x_l = 0 & \text{if } f > 0 \end{cases}$$

In scenario (ii), consumers prefer to make low skilled experts indifferent between high and low effort by always searching for matching opinions, i.e. $f = f_l^* = 0$. In this case, any solution for x_l within the defined interval that $x_l \in [\underline{x_l^*}, \overline{x_l^*}]$ is possible. Since $f > 0$ would lead to all experts choosing low effort, consumers strictly prefer to search for matching opinions as long as $V - p - 2\,\frac{s+d}{z} > 0$. However, if adaptation conditions (17) and (18) for low skilled experts are not fulfilled, $x_l \in [\underline{x_l^*}, \overline{x_l^*}]$ is not feasible and there will be a degenerate equilibrium.

(iii) *Scenario (iii)*

$$2c < p < 2c/(1-y) \rightarrow \begin{cases} x_l \in \{\underline{x_l}, \overline{x_l}\}, x_h = 0 & \text{if } f = f_l^* > f_h^* \\ x_h, x_l = 0 & \text{if } f > f_l^* \end{cases}$$

In scenario (*iii*), there is a great difference between low skilled and high skilled experts in their ability for diagnosis, i.e. y is relatively large. This implies that even while consumers can make low skilled experts indifferent between high and low effort, there is no possibility to achieve a perfect non-degenerate equilibrium, as high skilled experts will never choose high effort. For consumers choosing a mixed strategy with $f = f_l^* \in]0,1[$, (11) must hold with equality. Therefore, in equilibrium x_l can take only the extreme values of the determined interval $\{\underline{x_l^*}, \overline{x_l^*}\}$ with adaptation conditions for low skilled experts holding. With $V - p - 2\,\frac{s+d}{z} > 0$, consumers will opt for $f = f_l^*$ leading to a partial non-degenerate equilibrium with low skilled experts choosing $x_l \in \{\underline{x_l^*}, \overline{x_l^*}\}$ and high skilled experts choosing $x_h = 0$.

(iv) *Scenario (iv)*

$$2c < p = 2c/(1-y) \rightarrow \begin{cases} x_h \in [\underline{x_h}, \overline{x_h}], x_l = 1 & \text{if } f = f_h^* = 0 < f_l^* \\ x_l \in \{\underline{x_l}, \overline{x_l}\}, x_h = 0 & \text{if } f = f_l^* > f_h^* \\ x_h, x_l = 0 & \text{if } f > f_h^*, f_l^* \end{cases}$$

In scenario (*iv*), the difference in qualification between high and low skilled experts in comparison to relative price $p/2c$ is less extreme than in scenario (*iii*). Depending on adaptation conditions, consumers will choose either $f = f_h^* = 0$ or $f = f_l^* \in]0,1[$. In the former case, consumers search for matching opinions all the time, making high skilled experts indifferent between high and low effort and low skilled experts strictly preferring high effort. In the latter case, consumers play heir mixed strategy which makes high skilled experts to always choose low effort. In contrast, low skilled experts become indifferent between high and low effort, which would result in the same outcome as in scenario (*iii*). With $V - p - 2\,\frac{s+d}{z} > 0$, consumers strictly prefer any kind of non-degenerate equilibrium to a degenerate one. Notice that in the case that all adaptation conditions hold, consumers can choose freely between a partial and a perfect non-degenerate equilibrium. We show in the welfare section, that consumers prefer equilibria with $f = f(q)^* = 0$, since their welfare decreases in f. Consequently, consumers will opt for the perfect non-degenerate equilibrium in this scenario, if they can choose freely.

(v) *Scenario (v)*

$$p > 2c/(1-y) \rightarrow \begin{cases} x_h, x_l = 1 & \text{if } f < f_h^*, f_l^* \\ x_h \in \{\underline{x_h}, \overline{x_h}\}, x_l = 1 & \text{if } f = f_h^* < f_l^* \\ x_l \in \{\underline{x_l}, \overline{x_l}\}, x_h = 0 & \text{if } f = f_l^* > f_h^* \\ x_h, x_l = 0 & \text{if } f > f_h^*, f_l^* \end{cases}$$

In scenario (v), consumers are confronted with the same choices as in scenario (iv). However, note that in this scenario there is no possibility for an equilibrium with $f = f(q)^* = 0$. Again, consumers will adapt their behavior according to adaptation conditions. If all holds, they will opt for the equilibrium with the lower f, which will be a perfect non-degenerate equilibrium.

Appendix B - Further Calculations

Proof of conditions for non-degenerate equilibrium:

(i) Solving (11) reveals the possible values for $z \in \{\underline{z}, \overline{z}\}$

$$\begin{aligned} V - p - 2\frac{s+d}{z} &= zV - p - (s+d) \\ z^2 - \frac{z(V+d+s)}{V} &= -\frac{2(s+d)}{V} \\ z_1, z_2 &= \pm\sqrt{(\frac{V+d+s}{2V})^2 - \frac{2(s+d)}{V}} + \frac{V+d+s}{2V}. \end{aligned}$$

(ii) Building the f.o.c. for (11) determines the maximum value for s according to z

$$\begin{aligned} \frac{\partial \overline{s}}{\partial z} &= \frac{(V-2Vz)(2-z)+Vz(1-z)}{(2-z)^2} \stackrel{!}{=} 0 \\ &= (z-2)^2 - 2 \\ z_1, z_2 &= \pm\sqrt{2} + 2. \end{aligned}$$

Since $z \in [0,1]$, the only feasible solution is $z^* = 2 - \sqrt{2}$.

By inserting this into (11), we get the maximum value for $\overline{s}$

$$\begin{aligned} \overline{s}(z^*) &= \frac{V(2-\sqrt{2})(1-(2-\sqrt{2}))}{2-(2-\sqrt{2})} \\ &= V(3-2\sqrt{2}). \end{aligned}$$

Appendix C - Proof of Proposition 1

For any situation (d,p,z,f) being an equilibrium, all formerly defined market conditions need to be fulfilled. For an equilibrium to be a SBE, it needs to maximize overall welfare, given the market conditions, i.e. V, c and s, as well as given the market composition, i.e. a, y and k. It has been outlined that in any SBE $z \in \{\underline{z}, \overline{z}\}$ which requires $d = 0$. Moreover, $f = f_q^* \in \{\underline{f_q^*}, \overline{f_q^*}\}$ which requires that $p \in \{\underline{p}, \overline{p}\}$.

With adaptation conditions holding for low a low skilled equilibrium, given $p = \overline{p}$ and $f_l^* = \overline{f_l^*}$, the necessary value for z to make the situation a SBE, is determined by whether $\overline{p} > p^*$. If $p = \overline{p}$, it follows that $\overline{c} \leq \overline{p}/2c = (zV - s)/2$. From (37) follows that for $\overline{p} < p^*$, it is necessary that $\overline{c} > s/ay$. Using the second adaptation condition with $ay < z$, it follows that

$$\frac{zV - s}{2} > \frac{s}{z}$$

Solving for z gives

$$z_{1,2} = \frac{s}{2V} \pm \sqrt{\frac{s^2 - 8sV}{4V^2}}.$$

Since in any equilibrium, $\overline{s} = \frac{zV(1-z)}{2-z}$, there is no z which fulfills the condition. Consequently, $\overline{p} < p^*$ cannot be a low skilled equilibrium. However, with $p > p^*$ there is a potential low skilled SBE given by $(0, \overline{p}, \overline{z}(0), \overline{f_l^*})$

By a switch to a high skilled equilibrium, p^* increases. This enables an equilibrium with $\overline{p} < p^*$ while $f = f_h^*$ which requires $a(1-y) \geq 1-z$. Consequently, $(0, \underline{p}, \underline{z}(0), \underline{f_h^*})$ with $p < p^*$, $ay > z/(1-x_h^*)$ and $a(1-y) \geq 1-z$ is a possible high skilled SBE.

Assume a potential high skilled equilibrium with $p > p^*$, $ay > z/(1-x_h^*)$ and $a(1-y) \geq 1-z$. If this SBE is possible, it would result in $(0, \underline{p}, \overline{z}(0), \underline{f_h^*})$. However, if $a(1-y) \geq 1-z$ and $ay > z/(1-x_h^*)$, this requires that there exist an $y = y^*$ with

$$y^* = \frac{\overline{z}}{(1-\overline{z})(1-x_h^*) - \overline{z}}.$$

Notice that by assuming $a = (1-z)/(1-y)$, this implies $x_h^* = 0$ according to (16). With $x_h^* = 0$ it follows that $y^* = z$. Therefore, in order to be an equilibrium, this requires $y > z$. However, as simultaneously $a \geq (1-z)/(1-y)$ this leads to a contradiction, since $a \leq 1$. Consequently, $(0, \underline{p}, \overline{z}(0), \underline{f_h^*})$ cannot be an equilibrium.

Next, assume the potential high skilled SBE $(0, \overline{p}, \underline{z}(0), \overline{f_h^*})$. If this is possible, it follows from (37) that

$$z < z^* = \frac{2c(c(1-x_h)ay - s)}{(V-c)(p(1-y) - 2c)}.$$

Since $p = \overline{p} > 2c/(1-y)$, for $z < z^*$ it is necessary that $c(1-x_h)ay - s \geq 0$. Moreover, it requires that $\underline{p} \leq p \leq \overline{p}$. With $\partial\overline{p}/\partial s > 0$, it requires that $\underline{p} \leq \overline{p}$ at least if $s = \overline{s} = V(3 - 2\sqrt{2})$, which is the maximum amount for s in any equilibrium.[8] With $s = \overline{s}$, the former condition for $z < z^*$ becomes $c \geq \overline{s}/(ay(1-x_h)$. Inserting this into $\underline{p} \leq \overline{p}$ gives

[8]Notice that in order to be a flexible price equilibrium, $s \leq \frac{V(2\sqrt{5}-2)}{8+4\sqrt{5}}$ which is more restrictive than in the fixed case. However, our argumentation does not change by it.

$$\frac{2V(3-2\sqrt{2})}{(1-y)ay(1-x_h)} \leq \underline{z}V - V(3-2\sqrt{2}),$$
$$\frac{2(3-2\sqrt{2})}{\underline{z}-(3-2\sqrt{2})} \leq (1-y)ay(1-x_h).$$

Notice that by assuming that $s = \overline{s}$, $\underline{z}$ becomes independent of the actual value of V. Following this, $\frac{2(3-2\sqrt{2})}{\underline{z}-(3-2\sqrt{2})} > 1$ which results in a contradiction, as $(1-y)ay(1-x_h) \leq 1$. Consequently, $(0, \overline{p}, \underline{z}(0), \overline{f_h^*})$ cannot be an equilibrium.

Chapter 6

EXPERT QUALIFICATION IN MARKETS FOR EXPERT SERVICES: A SISYPHEAN TASK?

with Kilian Bizer

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

Tim Schneider[*†] *and Kilian Bizer*[*]

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; moral hazard; 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 $d = 2.20$ 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

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

[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.

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.

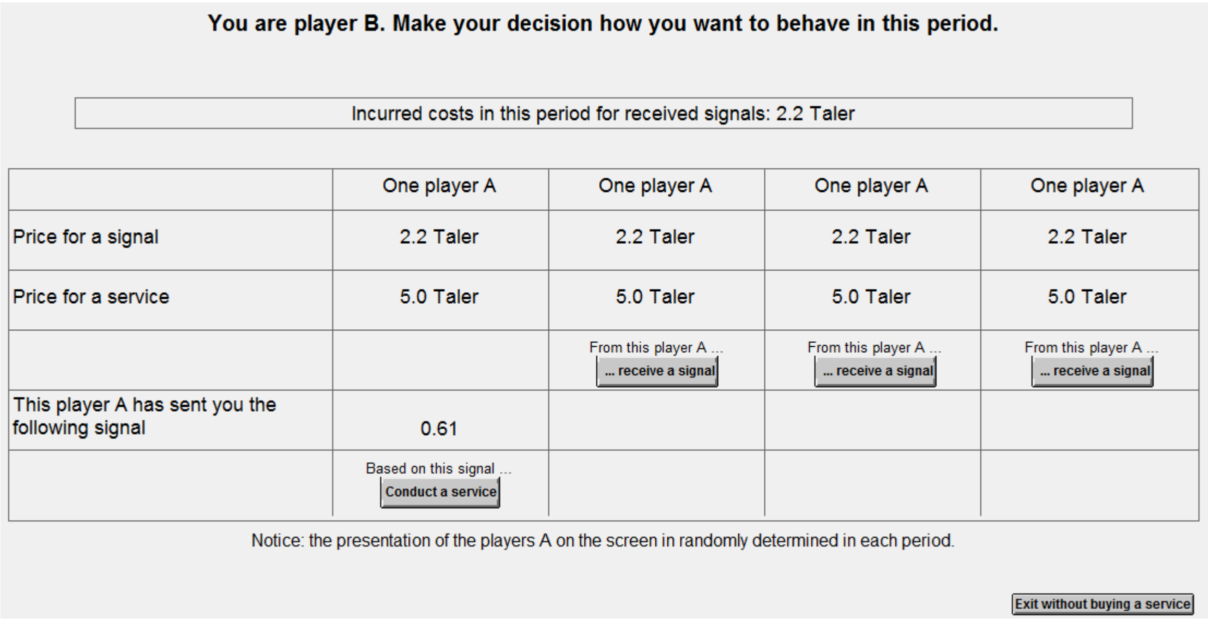


Figure 1: Consumers' decision screen.

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 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.

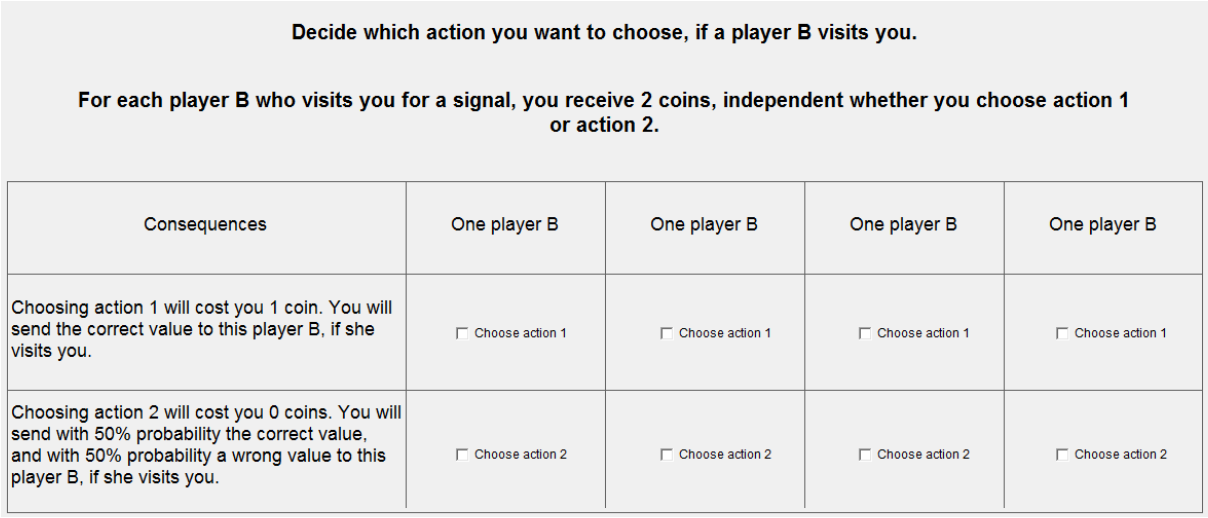


Figure 2: Experts' effort decision screen.

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.

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.

[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.

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]

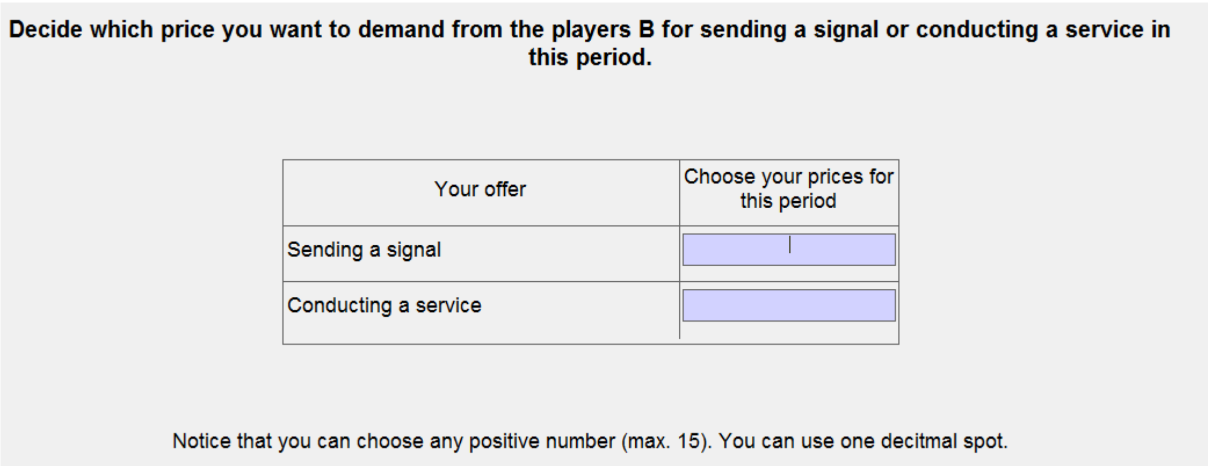


Figure 3: Experts' price decision screen.

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.

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.

[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.

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). 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 $a(1-y) \geq 1-z$.

[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.

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 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*

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

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).

□

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

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

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

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]

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.

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

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

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				
$\underline{z}/\bar{z}$: 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%

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 $z = \bar{z}$.

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.

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*

[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.

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.

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 ($p < 0.10$).

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

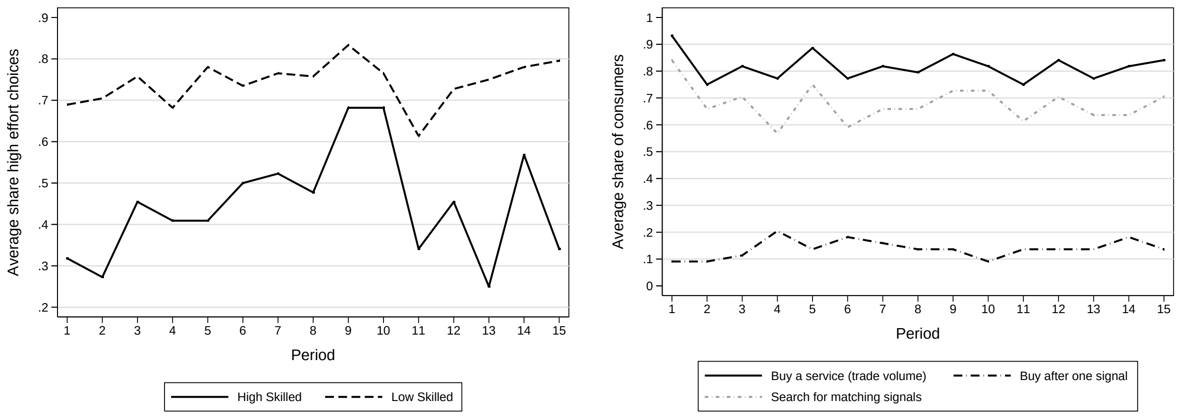
74.24% for low-skilled experts (WSR: 2.134, $p < 0.05$), which contradicts Hypothesis 1c. By comparing the different investment behavior of high- and low-skilled experts, we can confirm Hypothesis 1e in the baseline market, since experts significantly differ in their investments according to their type, 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' 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.

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.



(a) Experts effort choice (b) Consumer behavior

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

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 2*a*, 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

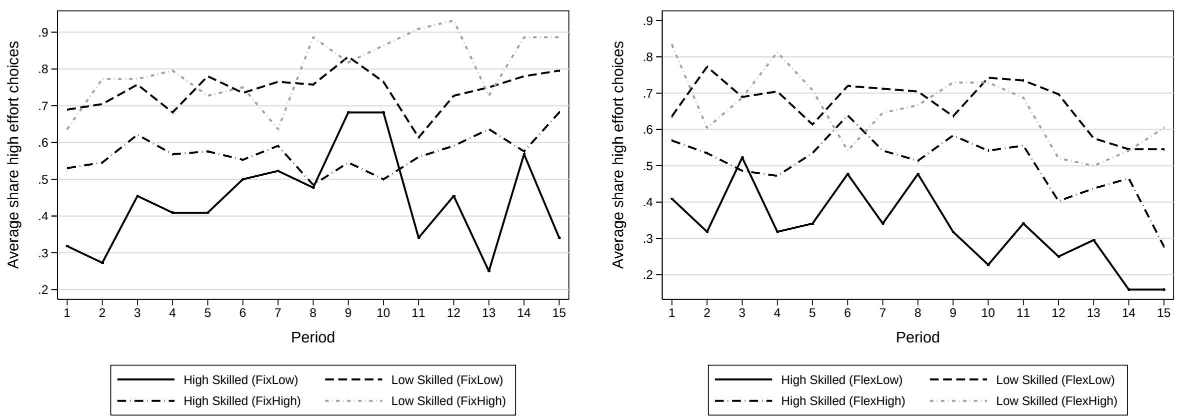
	FixLow	*FlexLow*	*FixHigh*	*FlexHigh*
Expert behavior				
z: Prob. correct signal	73.75% (.068)[cq]	66.78% (.085)[c]	78.90% (.071)[q]	72.74% (.111)
x_h: High effort high skilled	44.55% (.263)	33.03 %(.330)[q]	57.07% (.174)	50.37% (.201)[q]
x_l: High effort low skilled	74.24% (.061)[cq]	66.87% (.102)[c]	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* $z = -1.177$, $p > 0.23$).



(a) Fixed Prices (b) Flexible Prices

Figure 5: Expert Behavior across Treatments

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 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:

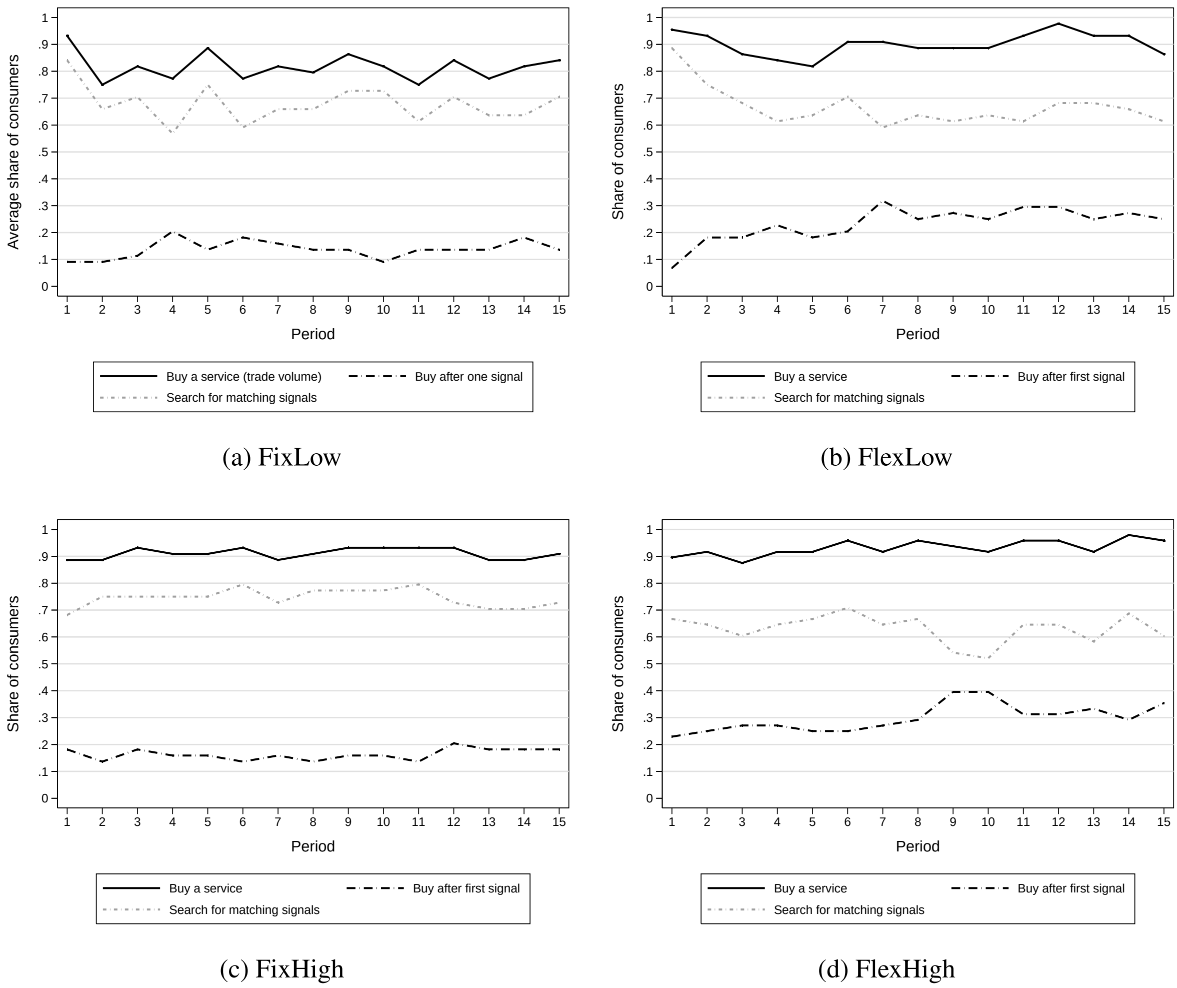


Figure 6: Consumer behvaior across treatments

$p < 0.05$). 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 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):

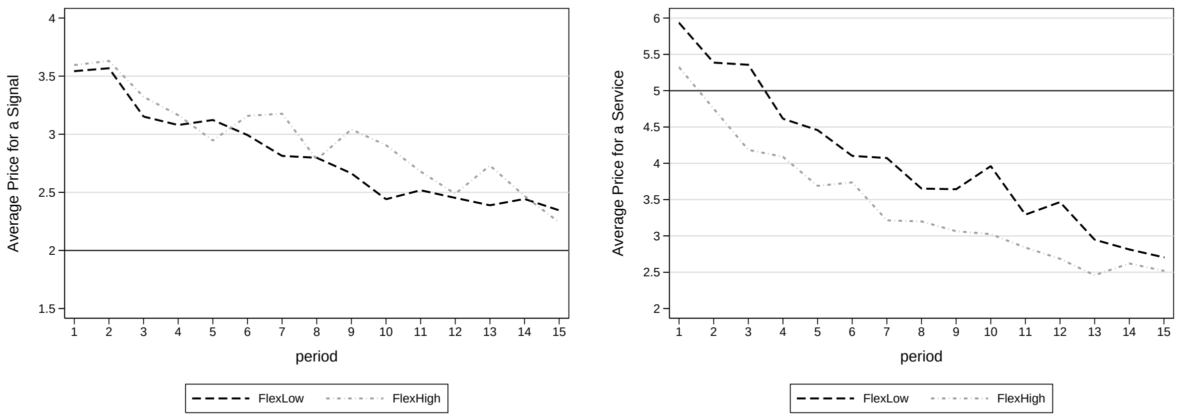
Experts: *Experts' investments decrease while remaining below their best response with fixed prices. With price competition, high-skilled experts invest too much and low-skilled experts too little, given actual prices and consumer behavior. These differences are mainly non-significant. The probability 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 3*a*. 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.
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. 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.

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.

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]

Summary payoff options for player A:

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 not 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 not 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.

Example of player A's payoff in a given period:
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:
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	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

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 not correct, you receive a payoff of 2.6 coins (= 12 coins - 5 coins - 2.2 $*$ 2).