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Can a bonus overcome moral hazard? Experimental evidence from markets for expert services

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by

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Can a Bonus Overcome Moral Hazard? Experimental Evidence from Markets for Expert Services[‡]

Vera Angelova* and Tobias Regner**

Abstract

Interactions between players with private information and opposed interests are often prone to bad advice and inefficient outcomes, e.g. markets for financial or health care services. In a deception game we investigate experimentally which factors could improve advice quality. Besides advisor competition and identifiability, we add the possibility for clients to make a voluntary payment, a bonus, after observing advice quality. While the combination of competition and reputation concerns achieves the highest rate of truthful advice, we observe a similar effect, when the bonus is combined with one of them. Thus, our results suggest that a voluntary component can act as a substitute for either competition or reputation, decreasing moral hazard.

JEL classification: C91, D03, D82, G20, I11

Keywords: asymmetric information; principal–agent; expert services; deception game; sender–receiver game; reciprocity; reputation; experiments; voluntary payment; competition

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1 Introduction

Moral hazard on the financial market is detrimental for consumers. Empirical evidence from the US shows that mutual funds offering higher broker commissions attract the most investments. However, higher commissions are related to lower investment performance (Christoffersen et al., 2013). Clients in Germany lose 50 billion euros per year due to misleading financial advice ('Die Welt', 2012). According to Mullainathan et al. (2012) retail financial advisors tend to give self-serving portfolio recommendations. An audit study focusing on the Indian life insurance market reports that life insurance agents recommend strictly dominated products which yield high commissions in up to 90% of the cases (Anagol et al., 2017). These market inefficiencies are due to asymmetric information (uninformed clients) and commission steering by funds (see Inderst and Ottaviani, 2012). In similar fashion, the health care sector which accounts for 15% of GDP in OECD countries (OECD, 2016) suffers from moral hazard and efficiency losses caused by information asymmetries.

Which factors could contribute to experts providing better advice and, in turn, to increased market efficiency?¹ We design a laboratory experiment to analyze the stylized relationship between expert advisors and clients in a controlled setting. As our experimental framework we use a deception game (Gneezy, 2005). We augment it with market forces (competition, the possibility to build reputation) and allow a voluntary action of the client, for instance, a bonus payment (at the end of the transaction after feedback about quality of advice has

¹See Angelova and Regner (2013), section 2, for the connection between advice quality and efficiency in the market of financial intermediaries.

been provided).

The key innovation of our design is to test whether a voluntary component can be a remedy against moral hazard, on its own and in interaction with instruments that have been studied before (competition and reputation). Huck et al. (2012) use a binary-choice trust game to analyze experience goods markets. They conclude that reputation based on quality provided in the past enhances trust and that competition reinforces this effect. Dulleck et al. (2011) analyze the richer framework of credence goods.

We use a 2x2x2 (competition, identifiability, option to pay a bonus) between-subjects design and model advice as an experience good. Its quality is unknown ex-ante but ex-post the client finds out whether the advice was good or bad. In reality, the quality of financial or medical advice may not be immediately observable. However, if clients do not need to solicit advice often, such that enough time can pass before their next decision is up, they may well be able to assess advice quality. Our design addresses this type of situations. Think of special medication that requires some time to show an effect but at the same time is only needed with low frequency. Likewise, in financial advice after some years a client will be able to compare the returns from a recommended long-term investment plan to the interest rate of a savings account or to a friend's portfolio (assuming similar risk structure). Moreover, we focus on markets where clients' access to advisors' past behavior is limited to own past observations, in contrast to centralized market platforms that allow easy access to an online history of transactions (e.g., ebay or Amazon).

Without competition, we find a significant increase in the rate of truthful advice when a

bonus can be given and advisors are identifiable. With competition, the rate of truthful advice is higher when a bonus can be given or when advisors are identifiable. Thus, the rate of truthful advice increases when multiple opportunities to reciprocate exist. This can be achieved in the time or client dimension. Identifiability leads to several client-advisor interactions over the course of the game and competition allows one advisor to have several clients who may reciprocate within one period.

Our results confirm previous findings in Huck et al. (2012): the combination of competition and reputation concerns achieves the highest reduction of opportunistic behavior. However, in real life settings implementing competitive environments or reputation mechanisms may not always be possible. Therefore, our results suggest that when one of these market forces is absent, a voluntary component can act as a substitute for it, decreasing moral hazard. In reality, the bonus could be thought of as any voluntary act that is costly to the client but would benefit the advisor as, e.g., spreading the word about the advisor on an online feedback platform or to family/friends.

The next section discusses the related literature. In section 3 we explain our experimental set-up, and state our behavioral predictions. In section 4 we present the results and discuss them. Section 5 concludes.

2 Related literature

Huck et al. (2012), henceforth HLT, use a repeated binary-choice trust game to analyze the effects of reputation and competition in a market for an experience good. They vary the extent with which trustors are informed about past behavior of trustees. There is either no, private (i.e. only about trustees a trustor has interacted with in the past) or public information (i.e. about all past interactions of all trustees). Moreover, trustors are either exogenously matched with a trustee (no-competition-treatment) or they can choose their preferred trustee based on her reputation (competition-treatment). HLT find that reputation enhances trust (but no difference between private and public information) and that reputation combined with competition eliminates the trust problem almost completely.²

Dulleck et al. (2011), henceforth DKS, study the effect of institutions (liability, verifiability), market forces (competition, reputation), and combinations of these on the provision of credence goods. In DKS's setting clients are uncertain about the quality they need. Sellers know what clients need, can offer either a low or high quality product (at a low or high cost) and charge either a low or a high price. After the transaction, buyers only learn whether quality was sufficient. With credence goods sellers can exploit clients in three ways, and DKS allow for all of them: undertreatment (providing insufficient quality), overtreatment

²Also Huck et al. (2016a) study markets for experience goods. They focus on the effects of price regulation and price competition. Buyers have full information about the quality provided by each seller in the past. Since we do not deal with price regulation and have implemented private and not public information, our study is only marginally related to theirs.

(providing quality that is not necessary), and overcharging (charging for a quality that was not provided). Reputation in DKS increases trade and decreases overcharging but does not decrease undertreatment and overtreatment, and has no effect on efficiency. Competition in DKS drives down prices and leads to maximal trade but has no effect on overtreatment, undertreatment, overcharging, and efficiency. When both competition and reputation are present, trade increases compared to the baseline but there is no further effect. DKS identify undertreatment as the main source of inefficiencies in their experiment.³

While all the previous studies use laboratory experiments, Schneider (2012), Rasch and Waibel (2018), and Balafoutas et al. (2013) test for inefficiencies in credence good markets directly in the field. Schneider (2012) takes a test vehicle to auto repair garages to check whether undertreatment, overtreatment, and overcharging occur and whether concern for reputation affects any of these (he signals either a motivation for a long lasting relation or a one-shot interaction). He finds that reputation does not improve outcomes. Rasch and Waibel (2018) complement the data from a field experiment similar to the one by Schneider (2012) with proxies for reputation and competition. According to their results, high competition decreases overcharging, while low concern for reputation increases it. Balafoutas et

³Two studies build on the analysis of DKS. Kerschbamer et al. (2017) focus on the role of social preferences in explaining why credence goods markets with verifiability do not reach efficient outcomes. Mimra et al. (2016) extend DKS by investigating the role of public vs. private information about experts and compare the effect of fixed versus endogenously chosen competitive prices. Another closely related study is Huck et al. (2016b) who find that competition partially offsets the negative overtreatment effect of insurance in a credence good market.

al. (2013) take a different perspective by looking at which customer characteristics lead to more overcharging in a field experiment with taxi rides.

To summarize, existing studies find some support for the effects of competition and/or reputation in experience/credence goods markets. Our contribution to this literature is to test for a novel potential remedy against moral hazard. We check whether a voluntary payment can be a substitute when one of the market forces is not available. Moreover, our study is the first – to the best of our knowledge – to analyze the effect of voluntary payments combined with competition and concerns for reputation in a repeated deception game.⁴

3 Experiment

We implemented an experimental deception game to study the effect of voluntary payments and market forces (competition, reputation) on the quality of the message. In our experiment we used a frame that we keep throughout the paper: we refer to sender and receiver as advisor and client, and the message was called recommendation. Subjects were randomly assigned a role of an advisor or client, which they kept for the whole experiment. The experiment consisted of 15 periods. At the beginning of each period, only the advisors learned which

⁴Other remedies against deception have been studied using variations of Gneezy's (2005) deception game: monetary rewards (Peeters et al., 2008), punishments (Sánchez-Pagés and Vorsatz, 2009), upfront and ex-post voluntary payments (Angelova and Regner, 2013), payoff disclosure (Ismayilov and Potters, 2013; Behnk et al., 2014), scrutiny (Van De Ven and Villeval, 2015). In Vanberg (2017) reputation building is possible but interests of players are aligned.

state of the world was realized. State here is another word for the allocation of options to payoffs (in our case payoff pairs). Options were called A, B, C, and D. The payoff pairs were (10, 5); (5, 10); (5, 2); (5, 2) with the payoff for the advisor listed first and that for the client second. The payoff pairs (10, 5) and (5, 10) created a reasonably strong conflict of interest between advisor and client, yet keeping total surplus equal to eliminate efficiency motives as an alternative explanation for deceiving or telling the truth. The additional two seemingly irrelevant payoff pairs yielding (5, 2) reduced the possibility for strategic truth-telling, see Sutter (2008). For this purpose, they were Pareto dominated by the other two options. They were both (5, 2) to keep it as simple as possible.

In the different states of the world, different payoff pairs were allocated to the same option. For instance, in one state of the world, option A gave 10 tokens to the advisor and 5 to the client; in another state, the same option yielded 5 to the advisor and 2 to the client. One possible state realization, as advisors saw it, is given in Table 1.

Table 1: A possible state realization

Option	Payoff for advisor	Payoff for client
A	10	5
B	5	10
C	5	2
D	5	2

Clients were informed about the possible payoff pairs, so that they were aware of the alignment of interests, as well as their own and the advisor's possible payoffs. However, clients

were not informed what state of the world was realized, i.e., which payoff pair was assigned to which option. They had to choose one option, based solely on the advisor's recommendation. There were four possible recommendations the advisor could give. For example, recommendation 1 read: "With option A you will earn the most." Instead of showing the recommended option to the client, she was asked whether she wanted to follow the recommendation. If the answer was yes, the recommended option was implemented as her decision. If it was no, one of the other three options was randomly selected to be implemented as her decision.

At the end of each period, both clients and advisors received feedback about which option was selected and their resulting payoffs. Advisors were also told whether the client followed the recommendation or not. Given the feedback about their own payoff, clients were able to infer the payoff of their advisor. They were also informed about advice quality when they decided not to follow. Only when they refused to interact, they did not learn anything about advice quality.

Payoffs from the chosen option were added to subjects' initial endowment of 2.5 tokens (paid in each period) to form the final payoff from the period. Two out of 15 periods were randomly selected and paid out in the end of the experiment. One group of 10 subjects (5 advisors and 5 clients) formed a matching group qualifying as one independent observation. When matching was exogenous (treatments without competition), we employed a random stranger matching protocol. Advisors/clients knew that over the 15 periods of the game they will meet each client/advisor, on average, three times.

In all treatments advisors were first asked to pick a fee they would like to charge for their

recommendation from the set of five possible fees: 0, 0.5, 1, 1.5, 2. After that they selected a recommendation based on the realized payoff table. Depending on the treatment, the fee was shown to either one particular client or to all clients within one matching group. In all treatments, the size (10 subjects), and the composition (5 clients and 5 advisors) of each matching group, as well as the matching protocol (endogenous or exogenous, if exogenous, then random, always clients with advisors) were common knowledge. An on-screen history box facilitated keeping track of one's own past interactions. It contained the period, the fee, the quality of the recommendation from the point of view of the client (good, medium, bad), and whether the client followed the advice. A final common feature of all treatments was that if a transaction did not take place, both the client and the advisor received their initial endowment (or outside option) of 2.5 ECU for this period.⁵

Thus, the stage game is a dynamic game, in which the advisor's strategy consists of two actions: choosing a fee for advice and choosing a recommendation. The client's strategy also consists of two actions: deciding whether to pay the fee and, if yes, whether to follow the advice. The natural sequence of decisions is the following. The advisor first chooses a fee, the client is then informed about the fee and decides whether to pay it. If not, the game ends and both players receive a payoff of 2.5 each. If yes, then the advisor sends a recommendation, and finally the client decides whether to follow that recommendation. We used the strategy method for advisors, i.e. we asked them to choose the fee and the

⁵The outside option was symmetric across roles to make sure it was not perceived as unfair, and low enough such that players had an incentive to interact. This last feature addresses types of advice where taking the outside option is not plausible, like for instance, a medical treatment that needs to be taken.

recommendation simultaneously and without knowing whether the client decided to pay the fee or not.

We employ a 2x2x2 full factorial design, with the factors competition, identifiability and the option to pay a bonus. Descriptions of the respective treatments follow. See Table 2 for an overview of the treatments. We ran two sessions per treatment. Each session consisted of 30 subjects, such that per treatment there were 60 subjects (30 advisors, 30 clients).

Table 2: Treatments overview and design details

	Without competition	With competition
Baseline	<i>Base</i>	<i>Comp</i>
Identifiability	<i>ID</i>	<i>CompID</i>
Bonus	<i>Bon</i>	<i>CompBon</i>
Identifiability & Bonus	<i>IDBon</i>	<i>CompIDBon</i>

Notes: 60 subjects and 2 sessions per treatment; exogenous matching in treatments without competition and endogenous matching in treatments with competition.

In treatments *Base* and *Bon*, advisors and clients were matched in pairs. Each advisor picked a fee, which was shown to her own client. If the client was willing to pay the fee, she would receive the advice, otherwise both the client and the advisor would earn their 2.5 tokens from this period. If the client got a recommendation, she would decide whether she wanted to follow it. After that, everyone received feedback about own earnings. Additionally, in *Bon*, clients would be able to offer a bonus to the advisor up to the amount of the client's total earnings in this period. The history of the period was summarized in the info box which in treatment *Bon* additionally listed the bonus paid/received.

In treatments *Comp* and *CompBon*, clients were informed about all fees in a random order.⁶ Based on the fees clients chose their preferred advisor for each interaction. While each client would choose maximally one advisor, each advisor could be selected by a number of clients between zero and five. It was common knowledge that independently of the number of interactions, each advisor would charge the same fee and send the same recommendation to all her clients.⁷ The total payoff of an advisor from a given period was equal to the sum of payoffs from all interactions in that period. At worst, an advisor would not be chosen for an interaction; her period-payoff in this case would be equal to her initial endowment. This initial endowment served as the safe outside option that advisors received independently of the treatment. The history box for advisors was augmented with two additional pieces of information: the number of clients served and how many of them followed the advice.

In treatments *ID* and *IDBon*, each advisor received a unique identification number. The history box was augmented by a column containing that identification number. It enabled clients to identify advisors they already interacted with. Clients did not receive any information about the quality of advice provided to other clients. Hence, the only information clients had about a particular advisor was based on their previous experience with that advisor.

Finally, in treatments with competition and identifiability (*IDComp*, *IDCompBon*), clients would pick an advisor based both on fees for advice and their previous experience with a

⁶Fees would be displayed in one row, but subjects knew that their order was determined by chance in each period, such that it was not possible to detect a particular advisor based on the position of her fee in the row.

⁷Since clients were not identifiable to advisors, it did not make sense to allow for discriminatory advice.

particular advisor.

3.1 Procedures

The experiment was conducted with University of Jena students. No disciplines were excluded, most of the subjects were German and 41% male. They were invited to the laboratory of the Max Planck Institute of Economics using the online recruitment system for economic experiments ORSEE (Greiner, 2004). The experiments were computer-based, using z-Tree (Fischbacher, 2007). Subjects earned 19.07 Euros on average and spent between 90 and 120 minutes (30 minutes of which on the instructive part) in the laboratory.

Upon arrival in the laboratory, subjects were randomly assigned to a cubicle, where they individually read the instructions (see Appendix E for a translation of the instructions and Appendix D for translated screen shots). During the experiment, eye contact was not possible. Although participants saw each other at the entrance of the lab, there was no way for them to guess with whom of the other 29 students they would be matched later on.

3.2 Behavioral Predictions

We begin with the analysis of the stage game and then we consider repeated game aspects in the identifiability treatments.⁸ We first discuss predictions under the standard self-interest

⁸The stage game is the game played in each of the 15 periods. Clearly, in the treatments without identifiability, subjects play a series of 15 one-shot games. In the treatments with identifiability, meeting the

assumption. Thereafter, we allow for social preferences in order to accommodate empirical evidence of honest behavior in similar settings. In the end, we state our hypotheses. All formal proofs are collected in Appendix A.

The subgame in which the advisor recommends an option (A , B , C , or D) and the client can decide between following (F) and not following (NF) is depicted in Table 3. It is always reached in equilibrium, because the client always chooses to pay the fee and enter the subgame instead of getting the outside option of 2.5. The subgame has three Nash equilibria in pure strategies, (A, F) , (C, NF) and (D, NF) , as well as an infinite number of Nash equilibria in mixed strategies. The advisor always charges the highest possible fee. For all subgame perfect equilibria in the stage game one can easily find supporting beliefs and the corresponding perfect Bayesian equilibria. In both subgame perfect equilibria in pure strategies, advisors are predicted to lie (i.e., recommend anything but option B) to their clients. Since bonuses are not contractible, in equilibrium, clients never pay a bonus, and advisors anticipate that a bonus will never be paid.

In the finitely repeated game with identifiability (but without competition), reputation concerns may affect the decision to advise truthfully or not. In treatments ID and $IDBon$, in addition to playing the stage game equilibria in each period, it is possible to construct equilibrium strategies, in which sending a truthful recommendation and following the advice the first time an advisor–client pair interacts can be part of a subgame perfect equilibrium.⁹

same opponent again turns the one-shot game into a repeated game.

⁹Recall that in this treatment an advisor can expect to meet a client 3 times during the 15 periods of the game. Hence, the client can use the credible threat of enforcing one of the equilibria (C, NF) or (D, NF)

Table 3: Subgame played after the advisor chooses a fee and the client agrees to pay it.

Advisor \ Client	F	NF
recommend A	(10; 5)	(5; 4.7)
recommend B	(5; 10)	(6.7; 3)
recommend C	(5; 2)	(6.7; 5.7)
recommend D	(5; 2)	(6.7; 5.7)

Notes: This table shows just an example for a possible assignment of options to payoff pairs. Recall that the payoff pair (10; 5) in the case of F can be assigned to any option A , B , C , or D .

In the identifiability treatments with competition, *CompID* and *CompIDBon*, clients can credibly threaten to stop interacting with advisors who do not tell the truth. The following strategies constitute a subgame perfect equilibrium in the finitely repeated game with competition and identifiability: advisors charge a fee of zero and send a truthful recommendation in all periods but the last one; clients ‘pay’ the fee, and follow the recommendation in all periods; if the advisor sends a truthful recommendation, the client selects the same advisor in the subsequent period, if not, the client switches to a different advisor. In the last period, the equilibrium (A, F) is played in the subgame.¹⁰

in the second and third interaction, if the advisor does not give truthful advice in the first. If the advisor gives truthful advice in the first interaction, then the client will enforce the more beneficial equilibrium for the advisor (A, F) in the last two interactions. See Appendix A1 for the formal proof.

¹⁰If all advisors follow this strategy, every advisor will interact with, on average, one client for 15 periods. If an advisor unilaterally deviates, she will lose her client(s) and earn only the outside option until the end

Summing up the predictions under the standard self-interest assumption, in the treatments without identifiability, in equilibrium advisors will never provide truthful advice and bonuses will never be paid. With identifiability but without competition, providing truthful advice in early periods can be part of an equilibrium. With identifiability and competition, giving truthful advice until the penultimate period can be part of an equilibrium.

However, related experimental studies (e.g., Gneezy, 2005; Cai and Wang, 2006; Sánchez-Pagés and Vorsatz, 2007; Hurkens and Kartik, 2009; Erat and Gneezy, 2012; Danilov et al., 2012; Angelova and Regner, 2013) frequently find less lying than predicted, a behavioral pattern known as “overcommunication phenomenon”. Social preferences are the widely accepted explanation for this behavior. More specifically, people may be lying less than standard theory predicts because of an aversion to lying, an aversion to feeling guilty because of disappointing the counterpart, or out of fairness concerns.

While several factors are known to affect the tendency to give truthful advice,¹¹ our experimental design focuses on reciprocity as the instrument to induce an additional motivation to tell the truth. In the spirit of Rabin (1993), Dufwenberg and Kirchsteiger (2004), Falk and _____ of the game, which is always less profitable than sticking to the equilibrium strategy. For the client it is also never profitable to unilaterally deviate, since in every period she gets the highest possible payoff; in the last period, an equilibrium is played. See Appendix A2 for the formal proof.

¹¹For instance, pre-play communication between the agents, in particular making a promise, has been found to reduce cheating (Charness and Dufwenberg, 2006; Beck et al., 2013). The relative monetary costs of lying seem to matter (Erat and Gneezy, 2012). Opportunities to reciprocate, especially if they are mutual, lead to more truthful advice in Angelova and Regner (2013).

Fischbacher (2006) the setting in the bonus treatments may trigger reciprocal behavior. Giving a bonus after following truthful advice emerges as an equilibrium, if subjects' sensitivity to reciprocate is large enough (see Appendix A3 for the formal proof). Hence, our design varies the scope for reciprocal concerns by allowing for a bonus or not. We allow advisors' reaction to a change of the scope for reciprocal concerns to be individually heterogeneous but assume that their reaction to such a change is equally distributed over treatments. Thus, on average, increasing the scope for reciprocity results in more truthful behavior.

3.2.1 Treatments without competition

In contrast to *Base*, in treatment *ID* reputation concerns may motivate advisors. Since they apply only to the first third of the experiment, we expect a relatively weak effect on truth-telling.

H1: The rate of truthful advice in ID is greater than in Base.

In treatment *Bon*, the possibility to give a bonus provides a one-sided opportunity (for the client) to reciprocate. Clients with high enough reciprocal concerns give a bonus after receiving truthful advice. Hence, a reciprocal interaction will result, if the advisor anticipates the client's bonus and decides to give truthful advice. Angelova and Regner (2013) find a sustainable positive effect of the combination of upfront voluntary payment and bonus afterwards.¹² However, they also report a positive effect but a decay over time if the bonus

¹²Angelova and Regner (2013) also compare the effects of same size voluntary vs. obligatory upfront

stands alone. In our design the bonus is the only voluntary component as the upfront fee is charged by the advisor and not voluntarily offered by the client. Hence, we cautiously expect a tendency among advisors to be more truthful.

H2: The rate of truthful advice in Bon is greater than in Base.

In treatment *IDBon*, honest advisors can be identified. A reciprocal relationship between an advisor and a client (truthful advice, bonus paid) in one interaction can now extend to subsequent meetings. While an advisor cannot reciprocate a received bonus to the particular client who gave it, he knows that he can expect to meet this client again in each future period with probability $1/5$. Thus, the advisor has a chance to reciprocate the paid bonus in expectations by giving truthful advice subsequently. In this way mutual opportunities to reciprocate arise. As a consequence, the positive effect of reciprocal concerns on the tendency to give truthful advice is amplified and we expect a higher rate of truthful advice than in the other treatments without competition.

H3: The rate of truthful advice in IDBon is greater than in Base, ID or Bon.

3.2.2 Treatments with competition

Treatment *Comp* serves as a baseline treatment within the set of the treatments with competition. In *CompBon*, clients with reciprocal concerns can return truthful advice within one interaction by giving a bonus. Thus, we expect an increased tendency to advise truthfully.

payments and find that voluntary payments lead to higher rates of advice implementation.

Moreover, in the competitive environment advisors are able to advise more than one client. As these clients might reciprocate truthful advice with a bonus, the incentive for telling the truth is amplified.

H4: The rate of truthful advice in CompBon is greater than in Comp.

If advisors are recognizable, telling the truth until the last period is an equilibrium. Therefore, we expect increased truth-telling and a drop in the rate of truthful advice in period 15.

H5: The rate of truthful advice in CompID is greater than in Comp.

In *CompIDBon* advisors are identifiable when competing for clients and clients can pay a bonus. As clients are able to select their advisor they likely pick the same advisor again after receiving truthful advice. Hence, the probability that an advisor faces again a client who gave a bonus before is likely more than $1/5$. In the extreme, an advisor-client relationship lasts for all 15 periods. Thus, stronger mutual opportunities to reciprocate between advisor and client are possible and this environment fosters reciprocity concerns among advisors. We expect that this reciprocity effect further strengthens the positive effect of reputation concerns on the tendency to give truthful advice.

H6: The rate of truthful advice in CompIDBon is greater than in Comp, CompBon or CompID.

4 Results

4.1 Choices of advisors and clients

Table 4 provides an overview of the average choices of advisors and clients.¹³ Advisors posted a fee of around 1, on average. Competition significantly lowers mean posted fees (1.13 in treatments without competition, 0.74 in treatments with competition, Wilcoxon-Mann-Whitney-Test, $p < .01$). The tests are always two-sided and based on six independent observations. Mean posted fees do not statistically differ from mean accepted fees in all treatments with competition but *Comp*, where the mean accepted fee is higher than the mean posted fee (Wilcoxon signed-rank test, $p < .07$).

In *Base* clients took the outside option in 9% of all transactions. This is the highest observed rate. In treatments without competition, the choice to take the outside option is positively correlated with the size of the requested fee. In treatments with competition, essentially no client decided to take the outside option.

The rate of truthful advice in *Base* is 27%, the lowest rate of all treatments. It is highest with identifiability of advisors and competition in the same treatment (74% in *CompID* and 75% in *CompIDBon*). Figure 1 depicts the rates of truthful advice over time. The left panel shows treatments without competition, the right panel those with competition. In all treatments without competition we observe a downward tendency over time. In the

¹³In Appendix B we provide a table with the outcomes in absolute numbers by treatment.

Table 4: Descriptive statistics

	Base	Bon	ID	IDBon	Comp	CompBon	CompID	CompIDBon
Average posted fee	0.98	1.08	1.07	1.39	0.93	0.83	0.65	0.59
Average accepted fee	1.08	1.14	1.15	1.47	1.01	0.79	0.52	0.55
No interaction (outside option taken)	9%	5%	7%	6%	2%	1%	1%	0%
Truthful advice	27%	33%	32%	56%	44%	62%	74%	75%
Follow	77%	88%	79%	91%	92%	95%	98%	98%
Bonus paid	–	34%	–	47%	–	48%	–	68%
Bonus paid, after following truthful advice	–	81%	–	83%	–	67%	–	78%
Average bonus	–	1.34	–	1.67	–	1.64	–	1.71
Truthful advice followed	19%	28%	25%	52%	48%	67%	81%	84%
Efficient outcome reached	25%	30%	29%	55%	50%	68%	82%	85%
Average profit of advisor	7.71	7.97	7.63	6.79	7.19	6.31	5.82	5.68
Average profit of client	5.81	6.29	6.09	7.57	7.28	8.23	8.98	9.17

competition treatments behavior is stable until the last three periods.

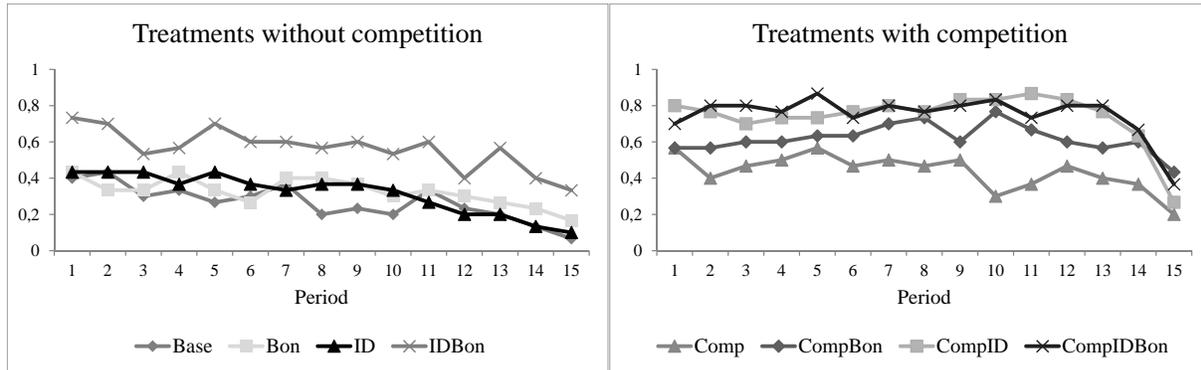


Figure 1: Truthful advice over time by treatment

In *Base* clients followed the advice in 77% of all interactions with an advisor. This is the lowest rate we observe across treatments. In *IDBon* as well as in all the competition treatments the follow-rate is above 90%.

In 34% of all *Bon* interactions clients paid a bonus and if they did, on average, this bonus was 1.34. In contrast, 68% of all *CompIDBon* interactions included a bonus and the average bonus was 1.71. Naturally, most bonuses were paid after clients followed truthful advice. Figure 2 illustrates the rate of bonus payments and their average size over time. We observe a substantial end-game effect in periods 14 and 15. The average bonus in period 15 drops down to 0 in *Bon*, 0.2 in *IDBon* and 0.3 in the treatments with competition. Before that the average bonus appears stable in treatments *CompBon* and *CompIDBon*. The large majority of clients paid a bonus at least once: over 90% in *Bon*, *IDBon*, and *CompIDBon*, and 77% in *CompBon*. Moreover, many clients frequently paid a bonus. The percentage of clients who paid a bonus more than half of the time was 60% in *IDBon* and *CompBon*, 80% in

CompIDBon, and 27% in *Bon*.

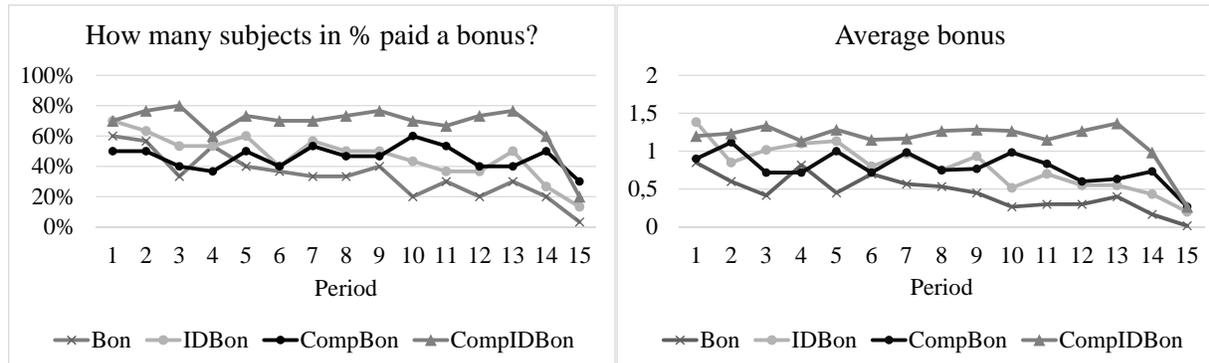


Figure 2: Percentage of bonus-payers and average bonus over time

With regard to efficiency, we compare how often the payoff pair (5, 10) resulted across treatments. While within the game self-serving and truthful advice both result in the same joint payoffs (assuming clients follow), in a broader sense not implementing the best option for the client implies an efficiency loss.¹⁴ The best option for the client may also result by chance, for instance, if the client does not follow untruthful advice. The efficient outcome reached is therefore a somewhat noisy measure. Hence, we also provide the rate of truthful advice followed as a proxy of efficiency across treatments. It is between 19% and 28% in *Base*, *Bon* and *ID*. In *IDBon* it is 52%, around the same level as in *Comp* (48%). In *CompBon* it is 67%. The highest rates of truthful advice followed are reached in *CompID* (81%) and *CompIDBon* (84%).

¹⁴This is due to advice steering in the commission system. Low-performing funds have higher incentives to pay commissions to financial intermediaries who, in turn, have an incentive to advise clients to invest in low-performing funds. See Inderst and Ottaviani (2012) for a formal model, and Angelova and Regner (2013), section 2, for details on the intuition.

The average profit of advisors is highest in *Bon*, *Base*, *ID*, and *Comp* (between 7.19 and 7.97), while clients in those treatments earn the least (on average between 5.81 and 7.28). In *IDBon*, *CompBon*, *CompID*, and *CompIDBon* we observe the reversed pattern: advisors earn least, between 5.68 and 6.79, and clients earn most, between 7.57 and 9.17.

4.2 Treatment comparisons

In order to test for treatment effects we set up a panel that contains all 3,600 interactions between advisors and clients. Table 5 reports the results of two logit mixed effects regressions with random terms associated with matching groups and advisors.¹⁵ The dependent variable is whether truthful advice has been given (1) or not (0). Explanatory variables are the fee posted by the advisor and dummy variables for the treatments. In order to control for the apparent negative time trend we include a dummy for the period and a dummy for the last period.

Specification 1 compares the treatments *Bon*, *ID* and *IDBon* to *Base*. We find a positive correlation between the posted fee and truthful advice (significant at the 1%-level). Neither the dummy for *Bon* nor the dummy for *ID* are significant. The dummy for *IDBon* is positive and highly significant. The coefficient of *IDBon* (2.39) is greater than the one of *ID* (0.81) or *Bon* (0.71) ($p < 0.05$). The period dummy as well as the dummy for the last period are negative and significant at the 1%-level.

¹⁵All reported results are robust to using standard random-effects logit models.

Specification 2 compares the treatments *CompBon*, *CompID* and *CompIDBon* to *Comp*. Again, the posted fee and truthful advice are positively correlated (1%-level). All treatment dummies are significant at the 1%-level. While the coefficient of *CompIDBon* (2.79) is greater than the one of *CompBon* (1.47) ($p < 0.05$), it is not significantly greater than the one of *CompID* (2.58). We do not find evidence for a negative time trend, only for a drop in the last period (significant at the 1%-level).

Table 5: Determinants of truthful advice

	(1) Without competition		(2) With competition	
Posted fee	0.88***	(0.1)	1.10***	(0.1)
Bonus	0.71	(0.7)	1.47***	(0.6)
Identifiability	0.81	(0.7)	2.58***	(0.6)
Identifiability + Bonus	2.39***	(0.7)	2.79***	(0.6)
Period	-0.16***	(0.02)	-0.00090	(0.02)
Last Period	-1.01***	(0.4)	-2.68***	(0.3)
Constant	-1.77***	(0.6)	-1.35***	(0.5)
Observations	1,800		1,800	

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; logit mixed effects regressions with random terms associated with matching groups and advisors; dependent variable: truthful advice (1 if given, 0 if not); reference category: *Base* in (1), *Comp* in (2).

The positive but non-significant effects of the *ID* and of the *Bon* dummy on truthful advice reject hypotheses 1 and 2. However, we do find a positive and significant effect of *IDBon*, thus supporting hypothesis 3. With competition all treatment dummies are positive and

significant. Hence, hypotheses 4 and 5 are supported. However, the *CompIDBon* treatment does not result in a significant increase of the rate of truthful advice in comparison to *CompID*. Hypothesis 6 is only partly supported.

To summarize, when there is no competition we find the hypothesized positive effect of a bonus only in combination with identifiability. It seems that additional interaction between client and advisor is necessary, that is, over periods as they know they will meet again and not only within a period. Under competition, as expected, identifiability as well as the bonus increase the rate of truthful advice. However, we do not find an additional positive effect when identifiability and bonus are combined.

We proceed with a test of treatment effects on the clients' decision to follow advice. Table 6 reports a set of logit mixed effects regressions. The dependent variable is whether the client followed the advice (1) or not (0). Hence, observations are dropped when the client decided against taking advice in the first place. Explanatory variables are the fee charged by the advisor, dummy variables for the treatments as well as the period and a last period dummy. Specification 1 presents results for the treatments without competition. Specification 2 adds a dummy whether in the previous period the client had a good experience, that is, whether she followed truthful advice. Specifications 3 and 4 show respective results for the competition treatments.

In the treatments without competition, both specifications yield similar results. The follow rate is positively correlated with the posted fee (significant at the 5% level). In *Bon* and *IDBon* the follow-rate is higher than in *Base* (significant at the 5% and 1% level, respec-

Table 6: Determinants of the decision to follow

	Without competition		With competition	
	(1)	(2)	(3)	(4)
Posted fee	0.28**	0.27**	2.63***	2.56***
	(0.1)	(0.1)	(0.5)	(0.5)
Bonus	0.80**	0.87**	1.33	1.60
	(0.3)	(0.4)	(1.0)	(1.0)
Identifiability	-0.010	0.063	2.03*	1.73*
	(0.3)	(0.3)	(1.0)	(1.0)
Identifiability + Bonus	1.19***	1.21***	2.76**	2.81**
	(0.4)	(0.4)	(1.1)	(1.1)
Period	-0.073***	-0.057**	0.16***	0.15***
	(0.02)	(0.02)	(0.04)	(0.05)
Last Period	0.14	0.083	-1.27*	-1.36*
	(0.3)	(0.3)	(0.7)	(0.7)
L.TruthfulAdviceFollowed		0.033		1.36***
		(0.2)		(0.4)
Constant	1.83***	1.64***	1.23	0.62
	(0.3)	(0.3)	(0.8)	(0.8)
Observations	1,678	1,469	1,778	1,641

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; logit mixed effects regressions with random terms associated with matching groups and clients; dependent variable: advice followed (1 if yes, 0 if no); L.x means the first lag of regressor x; reference category: *Base* in (1) and (2), *Comp* in (3) and (4).

tively). While the coefficients of *IDBon* are greater than the ones of *ID* ($p < 0.01$), they are not significantly greater than the ones of *Bon*. The more experienced a client gets, the less likely she is to follow the advice (the coefficient for ‘period’ is negative and significant at the 5% level at least). Whether the client made a good experience with her interaction in the previous period does not affect her decision to follow the advice in the current period.

In the treatments with competition, again the higher the fee the higher the follow-rate (significant at the 1% level). In *CompBon* the follow-rate does not differ from that in *Comp*. Clients in *CompID* are slightly more likely to follow the advice than in *Comp* (significant at the 10% level). However, in *CompIDBon* clients follow the advice significantly more often than in *Comp* (significant at 5%). The coefficients of *CompIDBon* are not greater than the ones of *CompID* or *CompBon*, though. In contrast to the treatments without competition, the more experienced clients get, the more likely they are to follow advice (significant at 1%). In the last period, the follow rate drops significantly ($p < 10\%$). Finally, having received truthful advice in the previous period appears highly important as it is positively correlated to the decision to follow (significant at the 1% level).

To sum up, fees are positively related to the follow rates independently of the treatment. Clients are more likely to follow the advice in those treatments, in which advisors are identifiable and bonus payments are possible at the same time. Without competition, the follow-rates decrease over time, while with competition, they increase. Positive experience with truthful advice from the previous period increases the probability to follow the advice in the current period only in the treatments with competition.

We continue with results about the role played by the bonus. Table 7 column 1 shows mixed effects regressions with the size of the bonus given by the client as the dependent variable. Explanatory variables are the fee charged by the advisor, a dummy variable whether in the previous period the client followed truthful advice, a dummy variable for treatment *IDBon*, respectively *CompIDBon*, as well as period and a last period dummy. Table 7 column 2 presents logit mixed effects regressions. The dependent variable is whether the advisor gave truthful advice (1) or not (0). The received bonus in the previous period replaces the followed truthful advice dummy as explanatory variable.

Results in column 1 confirm that the size of the bonus is negatively correlated with the fee. Whether the client followed truthful advice seems to have a positive effect on the size of the bonus. There appears to be a slight decay of the size of the bonus over time. In the competition treatments the bonus is significantly lower in the last period.¹⁶ Results in column 2 show that in the competition treatments having received a bonus in the previous interaction appears to have a positive effect on the tendency to give truthful advice. It seems that giving a bonus – induced by truthful advice – carries over to the next period. In the treatments without competition this is not the case.

Finally, we summarize our findings about the dynamics in the competition treatments (see Appendix C for a detailed analysis). When advisors are not identifiable, each serves approximately the same number of clients. In contrast, when advisors are identifiable, a few

¹⁶Alternative specifications with a bonus dummy, equaling 1 if a bonus was paid, as a dependent variable yield similar results.

Table 7: The role of the bonus

	(1) DV is bonus given		(2) DV is truthful advice	
	(1a) Without	(1b) With competition	(2a) Without	(2b) With competition
Posted fee	-0.22*** (0.04)	-0.29*** (0.05)		
TruthfulAdviceFollowed	1.26*** (0.05)	1.23*** (0.05)		
Identifiability + Bonus	0.20 (0.2)	-0.011 (0.2)	2.38** (1.0)	1.62** (0.7)
Period	-0.026*** (0.007)	-0.038*** (0.007)	-0.083** (0.04)	0.029 (0.04)
Identifiability + Bonus × Period	-0.013 (0.009)	0.013 (0.009)	-0.046 (0.05)	-0.093* (0.05)
Last Period	-0.050 (0.09)	-0.20** (0.09)	-1.21** (0.5)	-2.15*** (0.4)
L.Bonus			-0.041 (0.1)	0.49*** (0.1)
Constant	0.61*** (0.1)	0.51*** (0.1)	-0.89 (0.7)	0.43 (0.5)
Observations	850	892	840	840

Notes: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; (logit) mixed effects regressions with random terms associated with matching groups and clients/advisors; dependent variable: bonus in (1) and truthful advice in (2) (1 if given, 0 if not); L.x means the first lag of regressor x; observations are less than 900 due to no interactions (column 1) or because the first period drops out (column 2); reference category: *Bon* in (1a) and (2a), *CompBon* in (1b) and (2b).

manage to attract the majority of clients early in the game by posting low fees. Those successful advisors typically entertain long-term relationships with their clients by advising them truthfully.

4.3 Discussion

Overall, our findings document the effectiveness of bonus payments, and thus highlight the importance of pro-social motivational drivers like reciprocal concerns in interactions between players having asymmetric information and conflicting interests. A standard neoclassical modeling approach would not be able to explain the increased rate of truthful advice in *IDBon* compared to *ID*, and in *CompBon* compared to *Comp*.

The use of the bonus is relatively prevalent: across treatments between 34% and 68% of all transactions include a positive bonus. In treatments *IDBon*, *CompBon* and *CompIDBon* more than half of all clients paid a bonus in more than half of their transactions. For the bonus option to have an effect on the truthfulness of advice, multiple opportunities to reciprocate appear to be necessary. We find a significant increase of the rate of truthful advice only if clients interact with advisors not just within one period (*Bon*) but several times over the course of the game (*IDBon*, *CompIDBon*) or several clients can reciprocate within one period (*CompBon*). The condition of opportunities to reciprocate being mutual is consistent with the findings of Angelova and Regner (2013).

Keeping in mind that the experimental paradigms are different across DKS, HLT and our

study, we compare behavior in the baseline treatments (i.e. *B/N* in DKS vs. *control* in HLT vs. *Base* in our study), as well as behavior when both competition and reputation concerns apply (i.e. *CR/N* in DKS vs. *pi-c* in HLT vs. *CompID* in our study). In the baseline treatments, HLT report that trust is being honored in 28% of the cases, in our study the rate of truthful advice is 27% and in DKS sellers provide appropriate quality in 47% of the cases.¹⁷ With competition and reputation, HLT document an honor rate of 92%, we find truthful advice in 74% of the cases, while DKS report appropriate quality in 36% of the cases. Cheating being perfectly detectable in HLT and our study seems to be the most probable explanation for this difference to DKS. Note that Rubin and Sheremeta (2015) find a similar result in the context of reciprocity: when random shocks distort agent effort, wages and effort levels in their gift exchange game drop.

Finally, our setting differs from the trust game in HLT and the game in DKS in that cheating in our deception game is more pronounced. By choosing not to recommend the best option for the client, an advisor in our game explicitly tells a lie. If there is a moral cost to lying, subjects in our study could be expected to behave pro-socially more often than subjects in the other studies. Moreover, they could be more sensitive to incentives that lead them to lie less. However, the small differences between the results of HLT and our study do not indicate that moral costs of lying are substantial.

¹⁷Appropriate quality in DKS is 100% minus the rate of undertreatment. In order to provide an adequate comparison with our study where overtreatment is ruled out, we just consider the rate of undertreatment in DKS.

5 Conclusions

In a deception game (Gneezy, 2005), we study experimentally possible remedies against moral hazard, i.e. misleading advice given to clients. We introduce competition among advisors, the possibility for them to build a reputation, and a channel through which clients can reciprocate if they got truthful advice: a voluntary bonus paid after feedback about advice quality.

Without competition, mutual opportunities to reciprocate lead to the provision of significantly more truthful recommendations. They exist when the option to give a bonus is coupled with advisor identifiability allowing interactions over time not only within one period. In the competition treatments, the bonus or identifiability significantly increase the rate of truthful advice. However, we find no further increase when competition, bonus and identifiability are combined, possibly due to a ceiling effect.

Comparing our results to related studies of experience/credence goods, the combination of competition and reputation concerns also leads to the lowest rate of opportunistic behavior in Huck et al. (2012), while it has no effect in Dulleck et al. (2011). It seems that cheating being perfectly detectable – a common feature of our study and Huck et al. (2012) – is a pre-condition for a positive effect of reputation and competition.

Being able to rely on market forces like competition and reputation in order to foster efficiency seems reassuring. However, in real life settings implementing competitive environ-

ments and reputation mechanisms may not always be straightforward. For instance, the effect of ‘private’ reputation (based on clients’ own experiences) requires repeated interaction with the same advisor. Without anticipating a potentially long-lasting relationship with a client, advisors may not be willing to invest in reputation. Moreover, first-time clients are precluded from accessing information about the advisor altogether. Hence, if client-advisor relationships are relatively short-term, incentives to advise truthfully do not really kick in and ‘private’ reputation does not appear to be a useful instrument.

Thus, our result of a bonus effect points at a possible safeguard against opportunistic behavior in market environments where asymmetric information and conflicting interests would otherwise lead to inefficient outcomes. The voluntary act activates reciprocal concerns and, combined with the possibility of reputation building or having multiple clients, decreases cheating by advisors, increases the follow rate of clients, and leads to more efficiency.

What are potential applications of our ‘bonus’ in reality? Beyond the literal interpretation of an actual monetary payment of a content client to a truthful advisor, the voluntary act of the client could also be regarded as some additional effort of the client that will be beneficial to the advisor. The client’s contribution to an online feedback platform would be such a possible broader interpretation of our design’s voluntary component. Leaving feedback corresponds to an investment of time/effort on the side of the client, while the advisor benefits from a positive rating (in an indirect sense).

This is especially interesting since real life transactions in financial/medical advice are not centrally collected by automatized feedback tools (as is the case for online trading platforms

like ebay or Amazon). Instead of such an online history that provides ‘public’ reputation, information about advice quality is essentially limited to own observations and ‘private’ reputation. However, independent online platforms could gather feedback on a specific type of advice. Clearly, such independent platforms rely more on voluntary contributions of clients than centralized ones as leaving feedback is not just the matter of a mouse click. Our results indicate that some clients are willing to ‘pay back’ truthful advice, though. If clients’ potential effort can be channeled into collective feedback, access to ‘imperfect public’ reputation about the advisor would be possible. As a consequence, market efficiency under real life conditions (finding out on your own about advisors’ quality involves transaction costs, quality is multi-dimensional, relatively short time horizons) would benefit.

Generally, online review platforms/systems face a series of challenges.¹⁸ Facilitation of client feedback via a central entity, say, the health insurance system, could help overcome some of these issues. For instance, participation could be institutionalized and promoted by a reduction of the client’s insurance premium.

One limitation of our study is that cheating by advisors is modeled to be perfectly detectable. While this can be a realistic feature in some situations, it is not in others. For instance, the low returns from an investment can be due either to the recommendation of an unsuitable financial product or the weak economy. So, accounting for noise by adding a stochastic

¹⁸Naturally, not all clients would be willing to provide feedback on an external site and those who do may not be representative or even biased towards leaving negative feedback (see the literature on online ratings/feedback, e.g. Lafky (2014) or Lappas et al. (2016)).

component which can turn truthful advice into a bad outcome or bad advice into a good outcome, would extend the scope of our set-up.

Another limitation of our study is that we preclude discriminatory advice and do not allow clients to be recognizable for advisors. In reality, however, advisors are free to give different advice to different clients, whom they typically are able to identify. So, if clients are identifiable and discriminatory advice is allowed, then advisors can retaliate for truthful advice in the past that was not generously rewarded (with, e.g., a bonus) and reward generous (bonus) payments in the past with truthful advice now. In such a set-up, clients would also have incentives to build reputations in order to obtain truthful advice. Since the opportunities to reciprocate increase, we would expect that the rates of truthful advice will also increase. In particular, the difference in truth-telling between *CompIDBon* and *CompID* might become significant. Overall rates of truthful advice may increase, also in treatments where clients cannot reciprocate with a bonus, because it might be more difficult to deceive someone you already “know”. This aspect remains for future research.

References

- Anagol, S., S. Cole, and S. Sarkar.** 2017. “Understanding the Advice of Commissions-Motivated Agents: Evidence from the Indian Life Insurance Market.” *Review of Economics and Statistics*, **99(1)**: 1–15.
- Angelova, V., and T. Regner** 2013. “Do voluntary payments to advisors improve the quality of financial advice? An experimental deception game.” *Journal of Economic Behavior & Organization*, 93: 205–218.
- Balafoutas, L., A. Beck, R. Kerschbamer, and M. Sutter.** 2013. “What Drives Taxi Drivers? A Field Experiment on Fraud in a Market for Credence Goods.” *Review of Economic Studies* , 80(3): 876–891.
- Beck A., R. Kerschbamer, J. Qiu, and M. Sutter.** 2013. “Shaping beliefs in experimental markets for expert services: Guilt aversion and the impact of promises and money-burning options.” *Games and Economic Behavior*, 81: 145–164.
- Behnk, S., I. Barreda–Tarrazona, and A. Garcia–Gallego.** 2014. “The role of ex post transparency in information transmission – An experiment.” *Journal of Economic Behavior & Organization*, 101: 45–64.
- Cai, H., and J. T.-Y. Wang.** 2006. “Overcommunication in strategic information transmission games.” *Games and Economic Behavior*, 56(1): 7–36.
- Charness, G., and M. Dufwenberg.** 2006. “Promises and Partnership.” *Econometrica* 74(6): 1579–1601.

- Christoffersen, S. E. K., R. Evans, and D. K. Musto.** 2013. “What Do Consumers’ Fund Flows Maximize? Evidence from Their Brokers’ Incentives.” *The Journal of Finance*, 68: 201–235.
- Danilov, A., T. Biemann, T. Kring, and D. Sliwka.** 2013. “The dark side of team incentives: Experimental evidence on advice quality from financial service professionals.” *Journal of Economic Behavior & Organization*, 93: 266–272.
- ‘Die Welt’.** December, 2012. “Falsche Finanzberatung kostet Deutsche Milliarden.” *Die Welt*, Available at: <http://www.welt.de/newsticker/news1/article112238470/Falsche-Finanzberatung-kostet-Deutsche-Milliarden.html>
- Dufwenberg, M., and G. Kirchsteiger** 2004. “A theory of sequential reciprocity.” *Games and Economic Behavior*, 47(2):268–298.
- Dulleck, U., R. Kerschbamer, and M. Sutter.** 2011. “The Economics of Credence Goods: An Experiment on the Role of Liability, Verifiability, Reputation, and Competition.” *American Economic Review*, 101(2): 526–555.
- Erat, S., and U. Gneezy** 2012. “White Lies.” *Management Science*, 58(4):723–733.
- Falk, A., and U. Fischbacher** 2004. “A theory of reciprocity.” *Games and Economic Behavior*, 54(2):293–315.
- Fischbacher, U.** 2007. “z-Tree: Zurich Toolbox for Ready-Made Economic Experiments.” *Experimental Economics*, 10(2): 171–178.

- Gneezy, U.** 2005. “Deception: The Role of Consequences.” *American Economic Review*, 95(1): 384–394.
- Greiner, B.** 2004. “An Online Recruitment System for Economic Experiments.” In *Forschung und wissenschaftliches Rechnen 2003*, ed. Kurt Kremer, Volker Macho, 79–93. Goettingen: Gesellschaft fuer Wissenschaftliche Datenverarbeitung Bericht 63.
- Huck, S., G. K. Lünser, and J.-R. Tyran.** 2012. “Competition fosters trust.” *Games and Economic Behavior*, 76(1): 195–209.
- Huck, S., G. K. Lünser, and J.-R. Tyran.** 2016a. “Price competition and reputation in markets for experience goods: an experimental study.” *RAND Journal of Economics*, 47(1): 99–117.
- Huck, S., G. K. Lünser, F. Spitzer and J.-R. Tyran.** 2016b. “Medical Insurance and Free Choice of Physician Shape Patient Overtreatment. A Laboratory Experiment.” *Journal of Economic Behavior & Organization*, 131: 78–105.
- Hurkens, S., and N. Kartik.** 2009. “Would I Lie to You? On Social Preferences and Lying Aversion.” *Experimental Economics*, 12(2): 180–192.
- Inderst, R., and M. Ottaviani.** 2012. “Competition through Commissions and Kick-backs.” *American Economic Review*, 102(2): 780–809.
- Ismayilov, H., and J. Potters.** 2013. “Disclosing advisors’ interests neither helps nor hurts.” *Journal of Economic Behavior & Organization*, 93: 314–320.

- Kerschbamer, R., M. Sutter, and U. Dulleck.** 2017. “How social preferences shape incentives in (experimental) markets for credence goods.” *The Economic Journal*, 127: 393–416.
- Lafky, J.** 2014. “Why do people rate? Theory and evidence on online ratings.” *Games and Economic Behavior*, 87: 554–570.
- Lappas, T., G. Sabnis and G. Valkanas.** 2016. “The Impact of Fake Reviews on Online Visibility: A Vulnerability Assessment of the Hotel Industry” *Information Systems Research*, 27(4): 940–961.
- Mimra, W., A. Rasch and C. Waibel.** 2016. “Price Competition and Reputation in Credence Goods Markets: Experimental Evidence”. *Games and Economic Behavior*, 100: 337–352.
- Mullainathan, S., M. Noeth and A. Schoar.** 2012. “The Market for Financial Advice: An Audit Study”. *NBER Working Paper No. 17929*.
- OECD,** 2016. “OECD.stat” <http://stats.oecd.org>
- Peeters, R., M. Vorsatz, and M. Walzl.** 2008. “Rewards in an experimental sender-receiver game.” *Economics Letters*, 101: 148–150.
- Rabin, M.** 1993. “Incorporating fairness into game theory and economics.” *The American economic review*, 1281–1302.
- Rasch, A., and C. Waibel.** 2018. “What Drives Fraud in a Credence Goods Market?”

– Evidence from a Field Study.” *Oxford Bulletin of Economics and Statistics*, 80(3): 605–624.

Rubin, J., and R. Sheremeta. 2015. “Principal-Agent Settings with Random Shocks.” *Management Science*, 62(4): 985–999.

Sánchez-Pagés, S., and M. Vorsatz. 2007. “An Experimental Study of Truth-Telling in a Sender-Receiver Game.” *Games and Economic Behavior*, 61(1): 86–112.

Sánchez-Pagés, S., and M. Vorsatz. 2009. “Enjoy the Silence: An Experiment on Truth-Telling.” *Experimental Economics*, 12(2): 220–241.

Schneider, H.S. 2012. “Agency Problems and Reputation in Expert Services: Evidence from Auto Repair.” *The Journal of Industrial Economics*, 60: 406–433.

Sutter, M. 2009. “Deception through telling the truth?! Experimental evidence from individuals and teams.” *Economic Journal*, 119(534): 47–60.

Vanberg, C. 2017. “Who never tells a lie?” *Experimental Economics*, 20(2): 448–459.

van de Ven, J., and M. C. Villeval. 2015. “Dishonesty under scrutiny.” *Journal of the Economic Science Association*, 1(1): 86–99.

Appendix

Appendix A: Proofs of Propositions

A.1. Proof of Proposition 1

Proposition 1 The following strategies constitute a subgame perfect equilibrium in the thrice repeated game with identification but without competition: advisors charge a fee of 2, clients pay it; after observing the outcome (B, F) in the subgame of the first stage game, the Nash equilibrium (A, F) is played in the subgames of both subsequent stage games; after observing any other outcome in the first stage game, the Nash equilibrium (C, NF) is played in both subsequent stage games.

Proof. The payoff from not interacting for clients is equal to the initial endowment of 2.5. The payoff from interacting is at worst 2.5 (initial endowment of 2.5 less the highest possible fee of 2 plus the lowest possible payoff from advice, which is 2), hence clients always choose to interact. Advisors anticipate that and always charge the highest fee.

Now, consider in every stage game the subgame, in which the advisor recommends an option and the client decides whether to follow it. Assuming a discount factor $0 < \delta_a < 1$ for advisors and $0 < \delta_c < 1$ for clients, the continuation payoffs from the two stage games after observing (B, F) in the first stage game are

$$(10\delta_a + 10\delta_a^2; 5\delta_c + 5\delta_c^2) = (good_a, good_c),$$

while the continuation payoffs after any other outcome in the first stage game are

$$(6.7\delta_a + 6.7\delta_a^2; 5.7\delta_c + 5.7\delta_c^2) = (bad_a, bad_c).$$

Considering the thrice repeated game, we obtain the following payoff matrix:

Table 8: Payoffs in the thrice-repeated game

Client Advisor	F	NF
recommend A	$(10 + bad_a; 5 + bad_c)$	$(5 + bad_a; 4.7 + bad_c)$
recommend B	$(5 + good_a; 10 + good_c)$	$(6.7 + bad_a; 3 + bad_c)$
recommend C	$(5 + bad_a; 2 + bad_c)$	$(6.7 + bad_a; 5.7 + bad_c)$
recommend D	$(5 + bad_a; 2 + bad_c)$	$(6.7 + bad_a; 5.7 + bad_c)$

Notes: This table shows just an example for a possible assignment of options to payoff pairs. Recall that the payoff pair $(10; 5)$ in the case of F can be assigned to any option $A, B, C,$ or D .

The proposed strategy profile is a subgame perfect equilibrium of the thrice repeated game if:

$$5 + good_a \geq 10 + bad_a \Leftrightarrow 5 + 10\delta_a + 10\delta_a^2 \geq 10 + 6.7\delta_a + 6.7\delta_a^2 \Leftrightarrow \delta_a \geq 0.83$$

and

$$10 + good_c \geq 3 + bad_c \Leftrightarrow 10 + 5\delta_c + 5\delta_c^2 \geq 3 + 5.7\delta_c + 5.7\delta_c^2; \text{ this inequality is true for any}$$

$$0 < \delta_c < 1$$

The proposed strategy profile is a subgame perfect equilibrium for relatively patient advisors ($\delta_a \geq 0.83$), and for clients with any level of patience ($0 < \delta_c < 1$). We consider patience,

although this issue should not be relevant in experiments, since subjects are paid in the end (not after each period of the game). □

A.2. Proof of Proposition 2

Proposition 2: The following strategies constitute a subgame perfect equilibrium in the finitely repeated game with competition and identifiability: advisors charge a fee of zero and send a truthful recommendation in all periods but the last one; clients ‘pay’ the lowest fee, and follow the recommendation in all periods; if the advisor sends a truthful recommendation, the client selects the same advisor in the subsequent period, if not, the client switches to a different advisor. In the last period, the Nash equilibrium (A, F) is played in the subgame.

Proof. It is in the best interest of clients to interact, see Proposition 1. If clients select the advisor who requests the lowest fee, advisors will undercut the fees of their rivals until all end up charging the lowest fee of zero, like in a Bertrand competition.

Applying backward induction, we can compare the payoffs of players from using the proposed strategy to payoffs from unilaterally deviating from the proposed strategy. If all players stick to the proposed strategy and if each advisor serves one client in the first period of the game, then payoffs for advisors will be 5 ECU in every period from 1 to 14, and 10 ECU in period 15; clients will earn 10 ECU in each period until period 15, where they will earn 5 ECU. Every client will stick to her advisor in each period.

Given that clients will earn the maximum possible payoff in all periods but the last one, a

deviation is not profitable for them. A deviation in the last period is not profitable as well, since a stage-game equilibrium is played. Hence, it is in the best interest of clients to stick to the proposed strategy.

If advisors deviate from the proposed strategy in a given period, they will earn 10 ECU in this period. In every future period after the deviation, however, they will earn nothing, since their client will switch to another advisor.¹⁹ Hence, the deviation payoff for advisors is $\pi^D = 10$ and this payoff is always the same, independently of when advisors choose to deviate.

For the proposed strategy profile to be a subgame perfect equilibrium, the payoff from sticking to the strategy must be greater or equal to the deviation payoff. In the following, we state this condition for each period t and compute for which values of their discount factor δ_a ($0 < \delta_a < 1$) it is profitable for advisors to follow the proposed strategy. We denote the payoff from following the strategy in period t with π_t^S , which is equal to 5 ECU from the current period t plus the sum of all discounted future payoffs until the end of the game.

(i) $t = 15$: Deviation is not profitable since the stage-game Nash equilibrium (A, F) is played.

(ii) $t = 14$: $\pi_{14}^S = 5 + 10\delta_a \geq \pi^D = 10$. This holds for any $\delta_a \geq 0.5$.

(iii) $1 \leq t \leq 13$: $\pi_t^S = 5 + \pi_{t+1}^S \delta_a \geq 10$.

For $\delta_a \geq 0.5$, $\pi_{t+1}^S \geq 10$ (see (ii)) \Rightarrow for $\delta_a \geq 0.5$, $\pi_{t+1}^S \delta_a \geq 5 \Rightarrow$ (iii) will always hold for $\delta_a \geq 0.5$. Hence, deviating for advisors is not profitable in any period if $\delta_a \geq 0.5$. \square

¹⁹We ignore the symmetric initial endowment of 2.5 which both advisors and clients earn in each period.

A.3. Proof of Proposition 3

Proposition 3: In the bonus treatments, a ‘positive reciprocity’ equilibrium exists, in which the client gives a bonus and the advisor gives truthful advice.

Proof. In the following we focus on the two subgames that result when the advisor (AD) does not give truthful advice and the client (CL) follows (A, F) and after truthful advice and follow (B, F) . They are illustrated in Figure 3. In both cases the client can either give no bonus, No b , or give a bonus $b \in (0, 5)$. Predictions about behavior are a simple application of the model of sequential reciprocity by Dufwenberg and Kirchsteiger (2004).

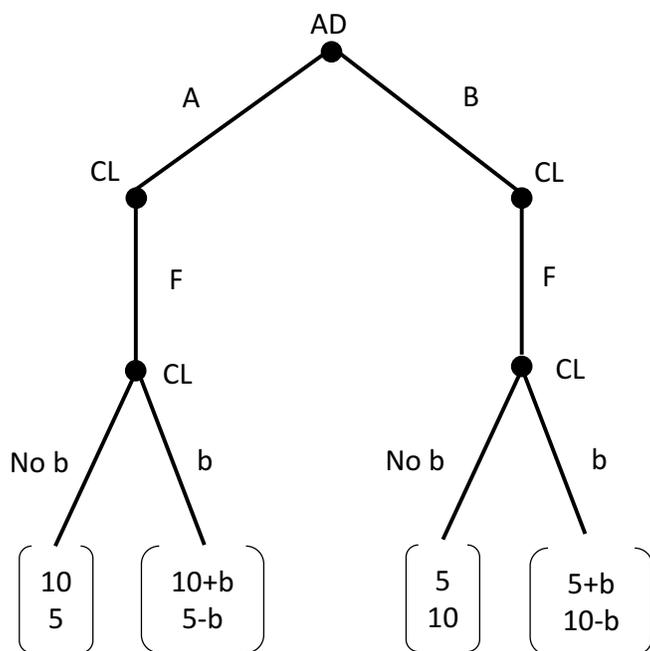


Figure 3: The two subgames that result after (A, F) or (B, F)

We interpret the equitable payoff of an individual as the average of the best and worst outcome based on the choices of the other. After (B, F) , the advisor’s equitable payoff is

$\frac{1}{2}(5 + (5 + b)) = 5 + \frac{1}{2}b$. Therefore, the client's kindness of giving a bonus equals $\frac{1}{2}b$, while kindness of not giving a bonus is $-\frac{1}{2}b$. We denote the client's belief of the advisor's belief about the client's choice after (B, F) by $\theta \in [0, 1]$. Then CL's belief about how much payoff AD intends to give to CL by giving truthful advice is $\theta(10 - b) + (1 - \theta)10$. The client's payoff after (A, F) equals 5 (assuming no bonus is given). Hence, the client's belief of the advisor's kindness from giving truthful advice is $\theta(10 - b) + (1 - \theta)10 - \frac{1}{2}((\theta(10 - b) + (1 - \theta)10) + 5)$ or $\frac{1}{2}(5 - b\theta)$.

We compare the client's utility from giving a bonus, U_c^b , to the utility if he does not give a bonus (U_c^{nb}) in order to determine conditions for the choice of a bonus; the parameter α_c represents the client's sensitivity to reciprocity.

$$U_c^b = 10 - b + \alpha_c \cdot \frac{1}{2}b \cdot \frac{1}{2}(5 - b\theta) > 10 + \alpha_c \cdot \left(-\frac{1}{2}\right)b \cdot \frac{1}{2}(5 - b\theta) = U_c^{nb}$$

$$-b + \alpha_c \cdot \frac{1}{4}b \cdot (5 - b\theta) > \alpha_c \cdot \left(-\frac{1}{4}\right)b \cdot (5 - b\theta)$$

$$\alpha_c > \frac{2}{(5 - b\theta)}$$

As in equilibrium beliefs must be correct, the condition must hold for $\theta = 1$: $\alpha_c > \frac{2}{(5 - b)}$.

It follows that if α_c is large enough the client's utility from giving a bonus (after receiving truthful advice and following it) is greater than his utility without giving a bonus.

Having established conditions for reciprocal behavior of the client, we now analyze, whether the advisor will ever give truthful advice in the first place (anticipating a bonus). The procedure is similar. We first compute the equitable payoff, this time the client's, assuming truthful advice is rewarded with a bonus but not untruthful advice. It is $\frac{1}{2}(15 - b)$. It follows that AD's kindness of untruthful advice is $-\frac{5}{2} + \frac{1}{2}b$ and kindness of truthful advice is $\frac{5}{2} - \frac{1}{2}b$. Denoting AD's belief of the client's belief about the advisor's choice after (B, F) by $\eta \in [0, 1]$, the belief of AD about CL's kindness of reciprocating is: $\frac{1}{2}(\eta(5 + b) + (1 - \eta)(10 + b) + \frac{1}{2}(\eta 5 + (1 - \eta)10) = \frac{1}{2}(-10\eta + 20 + b)$.

A comparison of AD's utility from giving truthful advice, U_a^t , and his utility when giving untruthful advice (U_a^u) tells us what the conditions for giving truthful advice are; the parameter α_a represents the advisor's sensitivity to reciprocity.

$$U_a^t = (5 + b) + \alpha_a \cdot \left(\frac{5}{2} - \frac{1}{2}b\right) \cdot \frac{1}{2}(-10\eta + 20 + b) > 10 + \alpha_a \cdot \left(-\frac{5}{2} + \frac{1}{2}b\right) \cdot \frac{1}{2}(-10\eta + 20 + b) = U_a^u$$

$$b + \alpha_a \cdot \left(\frac{5}{2} - \frac{1}{2}b\right) \cdot \frac{1}{2}(-10\eta + 20 + b) > 5 - \alpha_a \cdot \left(\frac{5}{2} - \frac{1}{2}b\right) \cdot \frac{1}{2}(-10\eta + 20 + b)$$

$$\alpha_a > \frac{1}{(-5\eta + 10 + \frac{1}{2}b)}$$

The condition must hold for $\eta = 1$ as in equilibrium beliefs must be correct: $\alpha_a > \frac{1}{(5 + \frac{1}{2}b)}$. If α_a is large enough, AD provides truthful advice (anticipating a bonus). As the denominator

is always positive, reasonable α_a values (> 0) for the condition result.

□

Appendix B: Data

Table 9: Outcomes by treatment in absolute numbers

Treatment	(A, F)	(C, NF)	(B, F)	(A, NF)	(B, NF)	(C, F)	no interaction	total
<i>Base</i>	235	0	80	74	18	1	42	450
<i>ID</i>	255	0	119	37	14	2	23	450
<i>Bon</i>	222	0	106	67	23	2	30	450
<i>IDBon</i>	152	0	232	29	7	3	27	450
<i>Comp</i>	190	0	215	20	15	1	9	450
<i>CompBon</i>	115	0	301	11	12	5	6	450
<i>CompID</i>	69	0	365	3	8	0	5	450
<i>CompIDBon</i>	61	0	380	1	6	0	2	450

Notes: Meanings of the abbreviations: *A*: the payoff pair (10,5) was recommended; *B*: (5,10) was recommended; *C*: (5,2) was recommended; *F*: the client followed the recommendation; *NF*: the client did not follow the recommendation; no interaction: the client chose the outside option.

Appendix C: Dynamics in the competition treatments

Table 10: Market shares in the competition treatments

	<i>Comp</i>	<i>CompBon</i>	<i>CompID</i>	<i>CompIDBon</i>
Highest market share	25%	27%	53%	49%
2nd highest market share	21%	24%	20%	25%
3rd highest market share	20%	20%	13%	16%
2nd lowest market share	17%	16%	9%	7%
Lowest market share	15%	12%	5%	3%

In the following, we compare advisors' market shares across the competition treatments, see Table 10. We calculated the market share (i.e. the number of clients served divided by the total number of clients in the matching group) for every advisor in every period. Next, we ranked the market shares from highest to lowest for each period and each matching group, such that for every period-matching group combination five market share categories (highest to lowest) result. Finally, we averaged the entries in each category over the periods and matching groups.

In the treatments where advisors are not identifiable, market shares are quite equal. This is not surprising because by design in these treatments clients can choose an advisor only based on posted fees, and identifying the possibly honest advisor from the previous period is unlikely. In contrast, when advisors are identifiable, market shares become very unequal.

For instance, in *CompID* market shares range from 53% (being the highest) to 5% (being the lowest). Obviously, some advisors manage to attract and keep the majority of clients.

What is the key to a large market share in the *ID* treatments?

For every matching group in the *ID* treatments we identified the advisor with the highest market share and analyzed her strategy regarding posted fees and advice quality. It turns out that two things are crucial for a large market share: first, to be selected to advise as many clients as possible already in period 1, and second, to keep advising truthfully.

Even if advisors in the *ID* treatments intend to give truthful advice, failing to attract clients in the beginning, puts them at risk of an empty store for the rest of the game, given that competitors remain honest, and thus their clients have no reason to switch. In early periods, the only way to attract clients is by choosing the ‘right’ fee, that is, the fee that will attract most clients. Table 11 gives an overview of the percentage of clients who chose the advisor with the lowest or the highest fee, both for period 1 and the entire game. Looking at period 1, in the *ID* treatments most clients (50–57%) pick the advisor with the lowest posted fee. Indeed, in both *ID* treatments, in period 1, the average accepted fee is significantly below the average posted fee.²⁰ Hence, the secret of attracting clients in the *ID* treatments seems to be posting a low fee in period 1. Notice, however, that for the *ID* treatments the column referring to the entire game is not very informative because a client may be choosing a high

²⁰In *CompID*, in period 1 the mean posted fee is 1.18, the mean accepted fee is .85; both differ significantly at the 3% level (Wilcoxon signed-rank test). In *CompIDBon*, in period 1 the mean posted fee is .87, the mean accepted fee is .72; both differ significantly at the 5% level (Wilcoxon signed-rank test).

fee not because she likes expensive fees but because this may be the only way to remain affiliated with the same advisor.

Table 11: Do clients select the advisor with the lowest fee?

	% of clients who selected the advisor with the lowest vs. highest fee	
	in period 1	in all periods
<i>Comp</i>	37% vs. 17%	28% vs. 32%
<i>CompBon</i>	40% vs. 17%	43% vs. 26%
<i>CompID</i>	57% vs. 20%	54% vs. 24%
<i>CompIDBon</i>	50% vs. 17%	44% vs. 28%

What is the key to keeping those clients? It is to give truthful advice period after period. Successful advisors maintain long term interactions with the same two or three (seldom four or five) clients. Most advisors give truthful advice until the very last period of interaction. In contrast, dishonest advice in one period leads to an immediate loss of clients, even if advisors have been honest for a number of periods before that. Similarly, most clients switch to a different advisor if their (although truthful) advisor starts increasing the fee (too much) compared to the own fee in previous periods and the fees of the other competitors in the same period.

In treatments without identification (*Comp* and *CompBon*), the only tool to attract clients is the posted fee. But what is the ‘right’ fee? In these treatments, in period 1 there is a tendency to choose the advisor with the lowest posted fee (37–40%) and not the one with the highest posted fee (17%), see Table 11. However, the remaining around 43%–46% of clients select

advisors who post any fee in between. Also, there is no significant difference between mean posted and mean accepted fees in period 1. Considering the entire game, the percentage of clients willing to pay the highest posted fee is higher than in period 1: 32% in *Comp* and 26% in *CompBon*. Indeed, in *Comp*, the mean accepted fee is significantly above the mean posted fee, when considering the entire game. It seems that in later periods in *Comp*, clients start to believe that paying higher fees gives them a higher chance to receive truthful advice. The regressions in Table 5 show indeed a positive correlation between posted fees and truthful advice. At least in treatment *Comp* clients realize this relationship. However, a large amount of clients chooses advisors who post anything between the highest and the lowest fee. So all in all, there is no consensus among clients which is the most attractive fee and, hence, advisors cannot really employ any clear strategy to attract clients.

Appendix D: Screenshots

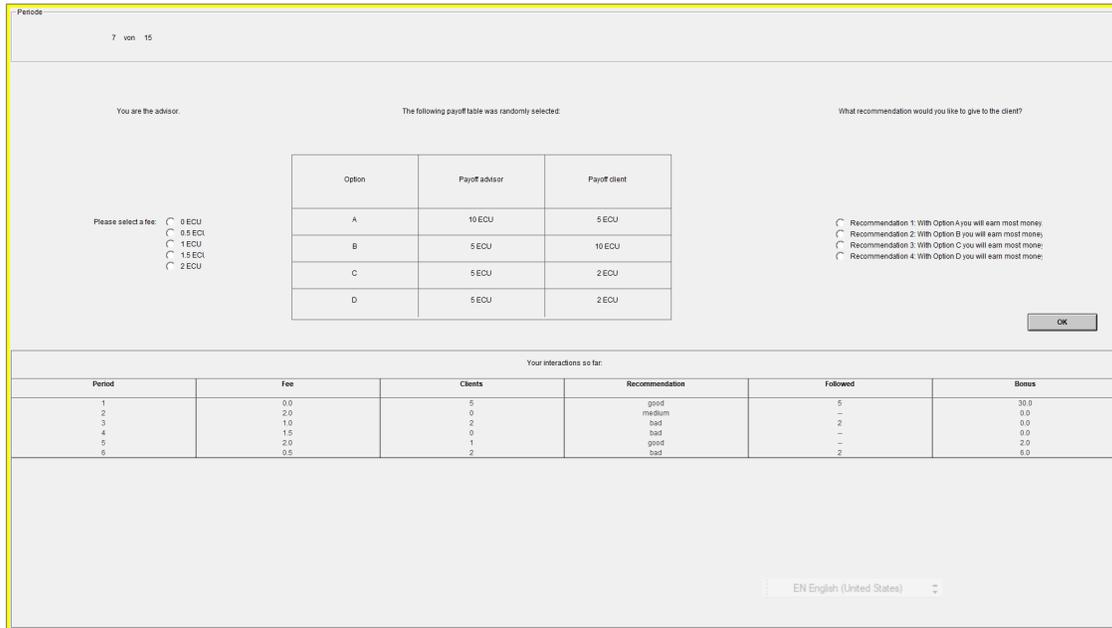


Figure 4: Translated screenshot for advisors in treatment *CompIDBon*

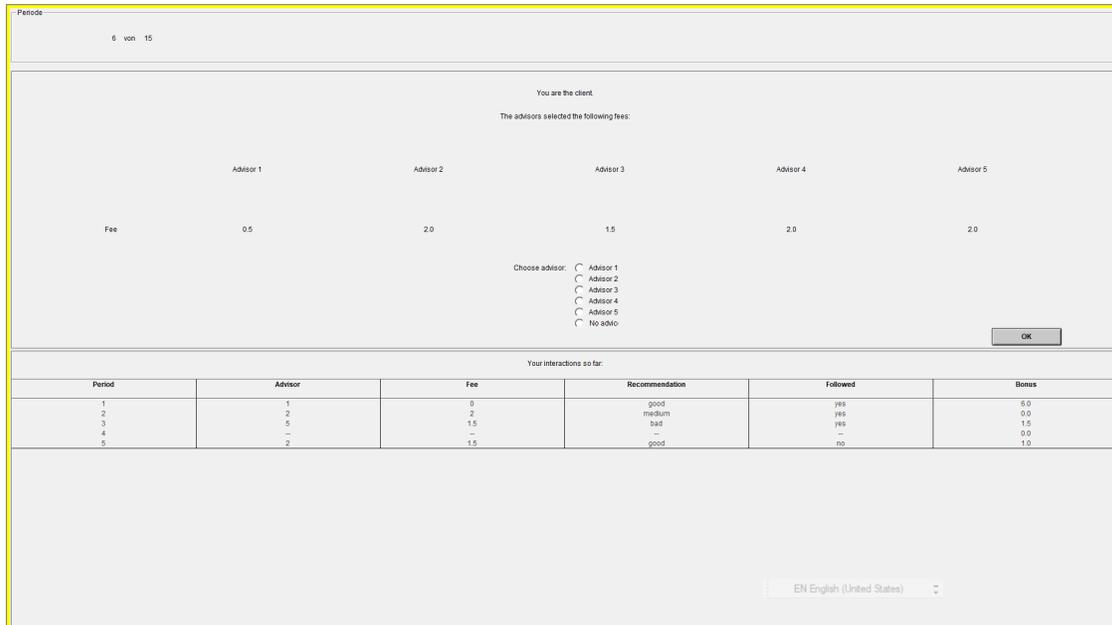


Figure 5: Translated screenshot for clients in treatment *CompIDBon*

Appendix E: Experimental Instructions

Baseline treatment (*Base*): main text (black)

Identifiability treatments (*ID*, *IDBon*, *CompID*, *CompIDBon*): additional red text

Bonus treatments (*Bon*, *IDBon*, *CompBon*, *CompIDBon*): additional green text

Competition treatments (*Comp*, *CompBon*, *CompID*, *CompIDBon*): additional purple text

Instructions

Welcome and thank you for your participation! In this experiment you can earn money depending on your decisions and those of the other participants. **It is therefore very important that you read these instructions thoroughly and carefully.**

Please note that communication among participants is prohibited throughout the entire experiment. If you have any questions, please raise your hand. We will approach you and answer your questions in private. Please do not ask your question(s) aloud. If you do not follow these rules, we will be forced to call off the experiment. Please turn off your mobile phones now.

These instructions are identical for all participants.

General Procedures

The experiment will last about 90 minutes. Each decision task will also be explained to you briefly on the computer screens. While you make a decision, other participants will make decisions as well which will possibly influence your payoffs.

You can earn money in this experiment. Your payoff will be calculated in ECU (Experimental Currency Units) and converted in EURO at the following exchange rate:

$$1 \text{ ECU} = 0.50 \text{ EURO}$$

In this experiment, 2 out of 15 periods will be chosen at random and you will be paid according to your decisions in these periods. At the end of the experiment, your earnings will be converted in EURO and paid to you in cash. Additionally, you will receive a show-up-fee of 2.50 EURO.

After filling out a questionnaire, the experiment will be over and you will receive your payment.

Here is an overview of today's session:

- Reading the instructions, answering control questions
- Decision tasks (15 periods)
- Questionnaire
- Payment and end of the experiment

Detailed Procedure

The experiment consists of 15 periods. In each period, two participants will interact with each other: **one advisor and one client**. At the beginning of the experiment you will learn which role was randomly assigned to you. You will keep this role until the end of the experiment. In each period another participant of your group will be **randomly and anonymously** assigned to you. In each group there will be 10 participants: 5 clients and 5 advisors. Nobody will learn the identity of the other participants.

Each advisor will receive a number that unambiguously identifies him/her throughout the experiment. There will be advisor 1, advisor 2, advisor 3, advisor 4, and advisor 5. The numbers of the advisors will be fixed, meaning that number 5 will always represent the same advisor. In each period the client will be informed about the number of the advisor currently advising him. Clients will not get any number.

Decision situation in each period

In each period, the advisor as well as the client will receive an initial endowment of 2.50 ECU. In each period, four payoff pairs will be available for selection with the first number denoting the payoff for the advisor and the second number - the payoff for the client (all numbers are in ECU):

(Payoff advisor, payoff client)
 (10, 5) ; (5, 10) ; (5, 2) ; (5, 2)

In each period, each of these payoff pairs will be assigned a name. There will be four names: Option A, option B, option C, and option D. **The names will be randomly assigned to the payoff pairs in each period.** That means that the payoff pair (10, 5) will sometimes be called option A, sometimes option B, sometimes option C, and sometimes option D. Hence, the best option, e.g., for the advisor will sometimes be A, sometimes B, sometimes C, and sometimes D.

In each period, only the advisor will know which option is assigned to which payoff pair. For instance, in one period the advisor may see the table on the bottom left, and in the next period he may see the table on the bottom right. Thus, in the first period, the most profitable option for the client will be option B, and in the next period, it will be option D.

Option	Payoff advisor	Payoff client
A	10	5
B	5	10
C	5	2
D	5	2

Option	Payoff advisor	Payoff client
A	5	2
B	5	2
C	10	5
D	5	10

The advisor can recommend an option to the client. In this case, the recommendation of the advisor will be the only information about the different options that the client will have. There will be four possible recommendations:

- Option A will earn you the most money.
- Option B will earn you the most money.
- Option C will earn you the most money.

- Option D will earn you the most money.

The client will then decide whether to follow the recommendation or not. If she does, the recommended option will be implemented as her decision. If not, the computer will randomly select one of the three options that were not recommended. The selected option will determine the payoffs for both, the client and the advisor.

Fee

The advisor can charge a fee for his recommendation. There will be five possible fees to choose from: 0 ECU; 0.5 ECU; 1 ECU; 1.5 ECU; 2 ECU. The client will decide whether she wants to pay the fee or not. Only if the client agrees to pay the fee, will she receive a recommendation. If the client does not agree to pay the fee, both client and advisor will receive only 2.5 ECU for that period. None of the four options will be paid out then.

The advisor will always be required to send a recommendation and to select a fee. The recommendation will be shown to the client only if she agrees to pay the fee. The option selected by the client will determine the payoffs for both the client and the advisor.

Bonus

After the client learns about her earnings in a period, she will decide how much bonus to pay to the advisor. The bonus can be any number between 0 and the client's total earnings in that period (initial endowment minus the fee plus the payoff from the selected option). The amount of the bonus will be subtracted from the client's earnings and added to the advisor's earnings. Advisors who advise several clients can potentially receive bonus payments from each of these clients.

Overview of the course of events in one period:

- 1) The advisor will set a fee and send a recommendation.
- 2) The client will be informed about the fees of all the advisors and the respective advisor's numbers. Then she will decide whether she would like to receive advice in exchange for paying the fee.
 - a) If yes, the client will decide whether to follow that recommendation.
 - b) If not, both client and advisor will receive 2.5 ECU.
- 3) Both client and advisor will learn how much they earned in this period.
- 4) The client will decide on the bonus she would like to pay to the advisor.

Table with your previous interactions

In the lower part of your screens you will see a summary of your interactions so far (see example on the next page). The name (in italics) and the content of the columns (in normal font) will be as follows:

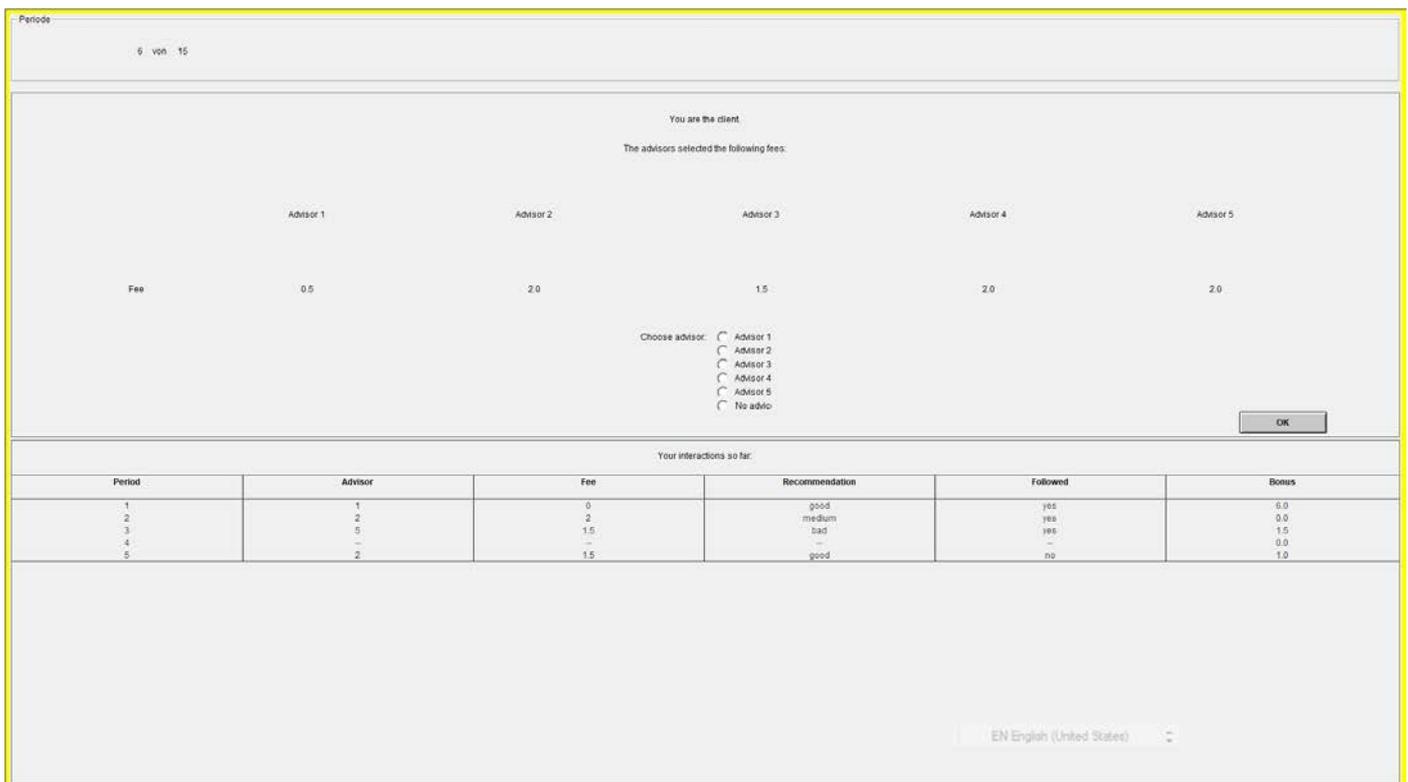
- *Period*: all previous periods except the current one
- *Advisor's number*: 1, 2, 3, 4 or 5
- *Fee*: amount which the advisor required for his recommendation: 0, 0.5, 1, 1.5, or 2
- *Recommendation*: the quality of the recommendation **evaluated from the point of view of the client**: either “good” (corresponds to 10 ECU for the client) or “medium” (corresponds to 5 ECU for

the client) or “bad” (corresponds to 2 ECU for the client) or “--“, if the client did not pay the fee and thus no interaction took place

- *Followed*: “yes” if the client followed the recommendation, “no” if not, “--“ if the client did not pay the fee and thus no interaction took place
- *Bonus*: the amount voluntarily paid to the advisor

Both advisor and client will see a table with their respective interactions. As an example, you can see here the decision screen of the client in period 6 with the table of all her previous interactions (**with the quality of the recommendation evaluated from the point of view of the client**):

[Screen shot for treatment CompRepBon:]



As an advisor you will see a table illustrating your perspective. It additionally will contain the number of your clients and how many of them followed your recommendation.

Earnings (2 out of 15 periods)

Your earnings in one period will be calculated as explained above: client and advisor will receive the payoffs from the realized payoff table. The advisor will possibly receive the fee and the bonus, which will be subtracted from the payoff of the client. Additionally, both will receive the initial endowment of 2.5 ECU. If an advisor advises several clients, from each interaction he will receive a fee and a payoff from the implemented option. However, only 2 out of the 15 periods will be payoff-relevant. These two periods will be determined at random at the end of the experiment. Your earnings will be paid to you in cash after you fill out the final questionnaire. Additionally, you will receive the show-up-fee of 2.5 EURO.