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Keeping a Clean Reputation: More Evidence on the Perverse Effects of Disclosure

Comments

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Previously titled "Competition and Coming Clean".

Keeping a Clean Reputation: More Evidence on the Perverse Effects of Disclosure

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Abstract

When a principal relies on an agent, a conflict of interest can encourage the agent to provide biased advice. Conventional wisdom suggests that such behavior can be reduced through disclosure requirements. However, disclosure has been shown to exacerbate self-serving bias and can actually lead to greater harm for the principal in one-shot interactions. But in many naturally occurring settings, agents form reputations, a mechanism that could diminish the incentive to provide biased advice. We test for bias in the advice agents provide when faced with reputation concerns, and examine the impact of disclosure in such an environment. In controlled laboratory experiments, we find little evidence of self-serving bias in the absence of disclosure when (1) agents form reputations and (2) principals use that information in selecting agents. However, we find the introduction of disclosure leads to self-serving biased advice that is difficult for principals to detect. When the conflict of interest is endogenous, we find that agents overwhelmingly put themselves in the position of having a conflict of interest, but principals neither avoid conflicted agents nor differentially discount the advice such agents provide.

Keywords: Conflict of Interest, Principal-Agent, Disclosure, Market Competition

JEL-Codes: *D82, G14, G18, I18, K12, L14, M55*

1 Introduction

Lawyers, financial advisors, doctors, and other agents are said to have conflicts of interest if their personal motivation is at odds with their professional responsibilities to serve their clients (Boatright, 2000a,b). While there are various policies in place regarding conflicts of interest, the literature reveals such conflicts are common and can undermine trust in professionals. For example, Scholl and Hung (2018) find there is generally low trust in financial professionals. They report that while 51% of consumers would prefer their adviser not have a conflict of interest, many consumers lacked awareness of financial advisers' responsibilities or their compensation structure. Agrawal and Chen (2008) find evidence that conflicts of interest cause bias the reports of stock analysts and that investors discount those reports. Ninety-four percent of doctors have a financial relationship with a pharmaceutical company, according to Campbell et al. (2007). They report that most (83%) doctors received gifts including meals from pharmaceutical companies, and many received funding for continuing education or conference attendance (35%) or payment for speaking or research activity (28%). Interestingly, Mainous (1995) finds that patients viewed personal gifts to physicians less favorably than office-use gifts, believing the former could impact the cost of care. Further, patients who believe physicians accept gifts from the pharmaceutical industry trust doctors significantly less than those patients who do not believe physicians accept gifts (Grande et al., 2012). Unsurprisingly, physicians believe that gifts from the pharmaceutical industry are less influential and more acceptable compared to patient attitudes (Gibbons et al., 1998). However sometimes it is the most knowledgeable consultants who have the most conflicts. Cooper and Golec (2019) found that when the FDA enacted stronger restraints on conflicts of interest, the expertise of their advisory panels sharply decreased.

The propensity for experts to behave in a manner that conflicts with the interest of the principal they represent has been established in economics through both lab and field experiments (see Kerschbamer and Sutter (2017) for a review of this literature). The conventional wisdom is that if a principal is aware of an agent's conflict of interest then the principal can take appropriate counteraction. As stated by Cain et al. (2005, p. 2), "Common sense suggests that recipients of advice will benefit from being more fully informed when they are made aware of an advisor's conflict of interest." This notion has led to widespread requirements for principals to disclose conflicts of interest, particularly in markets for "credence goods," where the agent is not able to determine the quality of service provided even after the fact.¹ While there is general support for

¹In some sense, the good used in our experiment can be viewed as an "experience good" since the principals eventually learn the true value of that good. However, the distinction of whether experience leads to knowledge of the true value of a good is not the key to assessing if one made the correct decision in our setting. Instead, what is relevant in our setting is the relationship between the value of the selected good and the value of the non-selected good. As our principals only receive a noisy signal of the value of the item not selected, it is difficult for them to ascertain if they made the best choice. Thus our setting has the

the disclosure of conflicts of interest, there is some debate about the potential impact. For example, a majority of patients report wanting to know if their doctor received a gift over \$100 from a pharmaceutical company, a majority also say their trust in their doctor would be undermined if they knew their doctor had received such a gift (Green et al., 2012). Rose et al. (2019) find that disclosing physicians' financial relations within the healthcare industry improved patient awareness of those relationships, but actually had no impact on the likelihood of attending an appointment or stated trust and confidence in physicians. In Massachusetts, a disclosure law reduced prescriptions for both branded and generic antidepressants, antipsychotics, and statins (Guo and Sriram, 2017). However, the 2012 Federal sunshine law had little impact on *average* payments from pharmaceutical companies to prescribers and instead led to higher payments to fewer doctors (Guo et al., 2017). Similarly, Chen et al. (2019) find that in states with laws requiring posted public disclosure, payments to physicians who accepted less than \$100 decreased. However, payments to physicians who accepted more than \$100 increased.

In a creative experiment, Cain et al. (2005) show that disclosure can exacerbate the problem introduced by a conflict of interest rather than reducing it. In their study, agents provided estimates of the value of a jar of coins to principals. Principals were paid based on the accuracy of their own guess as to the value of the coins in the jar, but agents who had a conflict of interest were paid based on how large the principal's estimate was. Cain et al. (2005) find that in the absence of disclosure, agents provide upwardly biased estimates. This bias leads principals to substantially overestimate the value of the coins. When the conflict of interest was disclosed to principals, the upward bias exhibited by agents did not decrease, but rather was dramatically *increased*. While the principals correctly anticipated agents would provide upwardly biased estimates, the principals badly underestimated the magnitude of the bias and thus the net effect of disclosure was actually harmful to the principals.

While the counterintuitive finding of Cain et al. (2005) suggests that it may be optimal to not disclose conflicts of interest, their setting is one in which there are no other pressures on the agents. Becker (1968) argues that when dishonest behavior has little to no cost it is expected to be prevalent; so, the observed bias in Cain et al. (2005) in the absence of disclosure is unsurprising. In contrast, Church and Kuang (2009) show that principals being able to directly sanction agents, then outcomes are improved. But, the sanctions introduced by Church and Kuang (2009) are meant to model repercussions like malpractice claims against doctors and thus are extremely severe. However, in many circumstances such dramatic sanctions are not practical or possible. As an example, a doctor may prescribe a medication produced by a company

fundamental characteristic associated with a credence good.

whose representative regularly gives the doctor gifts rather than a different medication that is more likely to be beneficial to the patient. But if the prescribed medication has an FDA indication for the diagnosed ailment, then a malpractice suit is unlikely to be successful. Still, many everyday circumstances do involve the potential for relatively small sanctions for those who are discovered to have acted upon a conflict of interest. Specifically, the fear of lost future opportunities that come with a negative reputation may be sufficiently costly to offset the conflicting interest.

The expected effect of maintaining a reputation is straightforward in cases where the principal can easily assess the performance of an agent *ex post*. For credence goods, such as those provided by a doctor, financial adviser, or lawyer, the effect is less obvious since assessing the agent is difficult, but Darby and Karni (1973) discuss how reputation and market forces can limit fraud for credence goods. Wolinsky (1993) presents a theoretical proof of how reputation and consumer search can be sufficient to discipline experts with conflicts of interest. However, the empirical support for the effectiveness of reputations is less clear. Pope (2009) finds patients select hospitals based on rankings, but not underlying quality measures of care. Hannan et al. (1994) argue providing rankings improves quality and decreases mortality rates for coronary artery bypass graft surgery. But, Mukamel and Mushlin (1998) find the rankings increased market share for low mortality surgeons and hospitals, leading to increased prices for the more highly demanded providers. Dranove et al. (2003) claim that medical rankings reduce consumer welfare, at least in the short term, as doctors attempting to improve their reputations elect to operate on healthier patients. In the financial domain, Gompers and Lerner (1999) found that reputation concern mitigates the impact of conflicts of interest in initial public offerings of stocks.

If reputation is sufficient to discipline agents, it is unclear if disclosure is socially desirable; the upside benefit is limited and disclosure could actually introduce self-serving bias in assessments. Of course, if agents exhibited biased assessments even in the presence of reputation concerns, then it is still possible that disclosure could be either beneficial, as typically assumed. Or disclosure could be harmful as suggested by Cain et al. (2005). Carl (2008) actually finds that disclosure of payments *increases* an agent's credibility when engaged in word-of-mouth product promotion, creating an opportunity for exploitation. Disclosure could also create confusion. For home mortgages, Ben-shahar and Schneider (2011) argue that people may not know how to use disclosed information and that they can only pay attention to so many things, so that it is better for the principals if they are focused on a limited number of key features of the decision.

We examine the impact of disclosure on self-serving bias in assessments by agents in a credence-good setting where agents have reputation concerns, using an experiment that draws on the basic Cain et al.

(2005) design. In our task, principals are forced to select between two options of unknown value (jars with indeterminate compositions of coins), but have to rely on an agent's assessment of the value of those options. Agents have a financial incentive to encourage a principal to select a particular option (jar of coins), but the agents also have an incentive for principals to choose to solicit their assessments. Principals receive a benefit based on the value of the selected option and also receive a noisy signal of the value of the non-selected option, both of which are independent of their agent's behavior. After their interaction principals can rate their agent and other principals can use the ratings when selecting an agent. In this way, the sanctions that we introduce differ from those in Church and Kuang (2009) in that our sanctions are in terms of reputation and are costless to the principal to impose and are more reflective of many naturally occurring interactions. There are two treatments in the main experiment: one in which the agents' conflict of interest is not disclosed to the principal and one in which it is disclosed. We measure bias as a systematic overstatement by the agent of the value of the conflicted option in comparison to the other option. Thus, our use of the term bias coincides with both the statistical definition and the colloquial one. We find that, when there is no disclosure we do not observe systematically biased assessments of values. But, like Cain et al. (2005), when disclosure is introduced we find that agents do provide systematically biased assessments of value and principals are unable to fully incorporate this fact into their decision making.

We also report an additional treatment in which the agent's conflict of interest is endogenous. That is, the agent decides to accept the financial incentive to encourage the principal to act in a certain way or not. The previous work by Cain et al. (2005) and Church and Kuang (2009) only considered exogenously imposed conflicts of interest and principals were unable to avoid conflicted agents. Given the previously discussed distrust of agents with conflicts, principals may try to avoid agents with conflicts of interest, which would discourage agents from putting themselves in such positions. However, it is also possible that principals are more willing to punish agents for providing bad advice when the agent opted to have a conflict of interest as opposed to when the conflict is unavoidable, which could discourage conflicted agents from providing bad advice and thus eliminate any real benefit to principals from avoiding such agents. Ultimately, we find no evidence that principals are more likely to select an agent without a conflict conditional on reputation score. Further, we do not observe any evidence that principals treated estimates from agents with and without conflicts of interest differentially despite conflicted agents providing more self-serving advice. However, there is some evidence that agents who opted to have a conflict of interest were rated more harshly when viewed as having provided self-serving advice.

2 Experimental Design and Hypotheses

In this section we lay out the experimental design including the task and procedures. We also present a simple theoretical model that serves as the basis for our hypothesis.

2.1 Main Experimental Task and Treatments

Our experiment varies whether or not the agents' conflict of interest is disclosed in an environment in which an agent's future earning can be diminished by an unfavorable reputation. In the main experimental task, a principal ("investor" in the subject interface) must select between two options labeled A and B. The options are jars of coins and the principal's value for an option equals the value of the coins in the associated jar. However, the principal cannot observe the jars directly and instead is forced to rely upon an assessment of the value of each option provided by an agent ("expert" in the subject interface). The agent has a direct incentive to encourage the principal to select option A, but also has an incentive to maintain a good reputation in order to be selected by other principals in the future as the game is played over multiple rounds. The rationale for using jars of coins is that the agent always has plausible deniability, even to the researcher, that the reported estimates of value match the agent's actual beliefs.²

A session of the experiment involved 12 subjects. Half of the subjects were randomly assigned the role of principal and half were assigned the role of agent. Once assigned, subjects retained their roles throughout the entire experiment, which lasted for multiple blocks of distinct rounds.

Table 1 lists the sequence of events within each round of the experiment. In Stage 0, subjects are randomly assigned to a group consisting of two agents and two principals. Additionally, the value of options A and B were assigned. In Stage 1, the agents observed two images of jars of coins (labeled "Jar A" and "Jar B").³ Figure 1 provides a sample of one of the images shown to agents in the experiment. After observing the images, each agent would provide an estimate for the value of the coins in each jar. In Stage 2 of each round after the first, principals see the mean number of stars each agent in the group has received over the course of the previous rounds in the current block. In the Disclosure Treatment, agents were also informed that the expert would earn an extra \$0.50 if the principal chooses Jar A. In the Baseline, no such disclosure was made although the agents still had the same conflict of interest. The presence or absence of the disclosure statement is the only difference between the two treatments.⁴ The principals then selected an agent, E . An

²This process is similar to Cain et al. (2005) who used jars of coins for the same reason.

³All subjects were informed in the instructions that every jar would contain between \$10 and \$25.

⁴In the first round of a block there were no previous ratings to display. For this reason, in the first round of a block each principal was assigned to a unique agent. This process ensured that an average rating could be calculated for all principals in all subsequent rounds of a block.

agent earned \$0.75 for each principal that selected the agent. In Stage 3, principals observed \hat{v}_A^E and \hat{v}_B^E which are the estimated values for Jar A and Jar B provided by the agent selected in Stage 2. Principals then select a jar. The principal’s agent earns an additional \$0.50 if the principal selects Jar A. In Stage 4, the value of the selected option, v_J^E , was revealed to the principal. Each principal also received a noisy signal of the true value of the jar that was not selected. The noisy signal was equal to $v_J^E + e_{it}$ where $e_{it} \sim \mathcal{U}[-\$2.00, \$2.00]$. Principals then rated their agent on a scale of 1 to 5 stars, with 1 star being the worst and 5 stars being the best. Each agent was informed of their own payoff, the number of principals who selected the agent, and the number of principals who selected the agent and subsequently selected Jar A. Agents were never informed of the true value of Jars A and B nor were they informed of their own reputation.⁵

Table 1: Sequence of Events within a Round

Stage	Active Role	Event	Payoffs	
			Agent	Principal
0 Set Up	Nature	Form Groups of 2 Principals and 2 Agents; Assign Jars A & B for Agents $I \in \{1, 2\}$ values, $\{v_A^1, v_B^1, v_A^2, v_B^2\}^a \in (\$10, \$25)$		
1 Estimate	Agents	Observe images of Jars A & B; Estimate the value of each jar $\{\hat{v}_A^1, \hat{v}_B^1, \hat{v}_A^2, \hat{v}_B^2\}$		
2 Select Agent	Principals	[NOT in Baseline: See disclosure statements] Observe Agents’ \bar{r}^I (★s) (except round 1) ^b Select Agent $E = \{1, 2\}$ (except round 1) ^b	+75¢(for E) ^c	
3 Select Jar	Principals	Observe selected Agent’s estimates, \hat{v}_A^E and \hat{v}_B^E ; Select Jar $J \in \{A, B\}$	If $J=A$ +50¢(for E) ^c	
4 Feedback	Principals	Receive signals, v_J^E and $v_{-J}^E + e_{it}$, ^d Rate selected Agent $r_t^E \in \{1, 2, 3, 4, 5\}$ (★s)		+ v_J^E
	Agents	See aggregate selections and own payouts		
5 Continue	Nature	Determine if block continues; ^e if yes, \bar{r}^I (★s) updated and go to Stage 0; if no, \bar{r}^I (★s) reset and block ends		

^a $v_A^1 = v_B^2$ and $v_A^2 = v_B^1$.
^b In Round 1, there are no ratings to show, and one agent is assigned to each principal, ensuring ratings in future rounds.
^c The agent who is not selected earns no payment.
^d $e_{it} \sim \mathcal{U}(-\$2, +\$2)$.
^e Starting in the 5th round, the block continued for another round with a 75% probability.

Stage 5 determines if a block continues for an additional round or not. For Rounds 1 through 4 of each block, once Stage 4 was completed the process returned to Stage 0 and repeated. However, starting in the

⁵These two design choices are meant to mimic situations like health care, where the doctor cannot know the true value of the outcome to the patient and where reputation is often informal.

Figure 1: Sample Image



5th round of a block, at Stage 5 the process returned to Stage 0 with a 75% chance and the block ended with a 25% chance. Thus, the horizon of the block was indefinite although subjects knew the stochastic nature of the termination. Importantly, reputations did not carry over between blocks. Thus, a new block offered an agent a chance to start over. This was done out of concern that an agent who formed a bad reputation early might never have the chance to improve it in later rounds since only selected agents are rated. A single set of realizations was drawn and used to determine the duration of each block for all sessions in both treatments. Ultimately, there were four blocks lasting a combined 29 rounds. Agents were paid their cumulative earnings for two randomly chosen blocks whereas principals received the value of the jar selected in one of the 29 rounds chosen at random.

2.2 Additional Experimental Details

The jars that were used contained mixtures of quarters, dimes, nickels and pennies. The actual values of the contents ranged from a low of \$13.32 to a high of \$22.43 with a mean value of \$17.77. Jars contained between 175 and 466 coins each. In the instructions it was demonstrated that volume was not a good indicator of value of coins. The intention was that each image would be used as both Option A and Option B during the course of the experiment although not in the same round to control for jar-specific characteristics. However,

due to a programming error, some images were treated as Option A twice or as Option B twice for some subjects. Therefore, the analysis presented in the next section is limited to cases where an image was used both for Option A and Option B over the course of the experiment.⁶

The experiment was implemented via oTree (Chen et al., 2016) and conducted at the Economic Science Institute at Chapman University. A copy of the instructions is included in Appendix A.1. Subjects were recruited from the lab’s standing pool of volunteers and none of the subjects had participated in any related study. Each session lasted up to 90 minutes, and subjects earned an average of \$23.30 including a \$7 participation payment. For both the Baseline and the Disclosure Treatment, three sessions were run involving a total of 72 subjects.

Guessing the correct value of the coins is challenging. As a demonstration, we encourage the reader to guess the value of the coins shown in Figure 1 before reading the footnote for this sentence.⁷ Therefore, a separate study was conducted to calibrate error in estimating the value of each jar of coins. We refer to this separate study as the Guess Experiment. Twenty-four subjects participated in the Guess Experiment in a single session at the Economic Science Institute. This session lasted 30 minutes and relied on volunteers from the same subject pool as the main experiment although no one was allowed to participate in both the Guess Experiment and the main experiment. Subjects in the Guess Experiment observed the full set of images used in the main experiment, and a quadratic scoring rule was used to incentivize truthful reporting of the value of the coins in each image.⁸ The average earnings in the Guess Experiment were \$14.58 including the \$7 participation payment.

2.3 Theoretical Model

Levitt and List (2007) present a model in which the utility of agent i for an action has additively separate terms for the moral component, M_i , and the financial component, W_i . Specifically, they posit

$$U_i(a, v, n, s) = M_i(a, v, n, s) + W_i(a, v)$$

where a is the action, v is amount of money at stake, n capture societal norms or laws, and s is the scrutiny the action will receive. For an immoral action the first term will be negative. However, if the second term is greater than the first, the immoral action will bring agent i a net increase in utility and the agent will take the action.

⁶Results that include all estimates are not qualitatively different. See Appendix A.2.

⁷The jar shown in Figure 1 contains \$17.73.

⁸Subjects earned \$25 - \$2(guess - true value)² each round, and were paid their average earning over all rounds.

In this model, an increase in scrutiny for a given norm increases the moral cost but it has no impact on the financial benefits (i.e., $\frac{\partial M_i}{\partial s} < 0$ and $\frac{\partial W_i}{\partial s} = 0$). Thus, disclosure to the principal that agent i earns a bonus if the principal chooses one option but not the other should increase the moral scrutiny of the estimates i reports, which would discourage immoral action by the agent. With the introduction of a reputation the financial term could also depend on both n and s as well (i.e., $v = f(n, s, \dots)$). In such a setting an immoral action leads to both greater moral costs and reduced financial benefit (i.e., $\frac{\partial M_i}{\partial s} < 0$ and $\frac{\partial W_i}{\partial v} \frac{\partial v}{\partial s} < 0$). This would make disclosure even more attractive for principals.

However, Cain et al. (2005) speculate that disclosure may actually create a “moral license” to engage in otherwise socially unacceptable behavior. Effectively, this line of reasoning posits that since the principals have been warned, they should expect agents to engage in self-serving behavior and account for this when making their own decisions. This line of reasoning is similar to the old adage of *caveat emptor*. In terms of the model by Levitt and List, moral licensing alters the norms, n , such that the immorality of an action is reduced (i.e., $M_i(a, v, n_{disclosure}, s) > M_i(a, v, n_{nondisclosure}, s)$). If true, the net effect of such moral licensing is ambiguous, and disclosure could lead to more or less self-serving behavior. This ambiguity is true even when taking reputation into account, because the financial harm from an immoral action could be reduced as the norm changes.

Based on this model, our experiment seeks to answer the two following questions which serve as the main hypotheses to be tested. First, will agents exhibit a self-serving bias in the presence of reputation concerns? Second, will the disclosure of the agent’s conflict of interest lead to more self-serving bias on the part of agents?

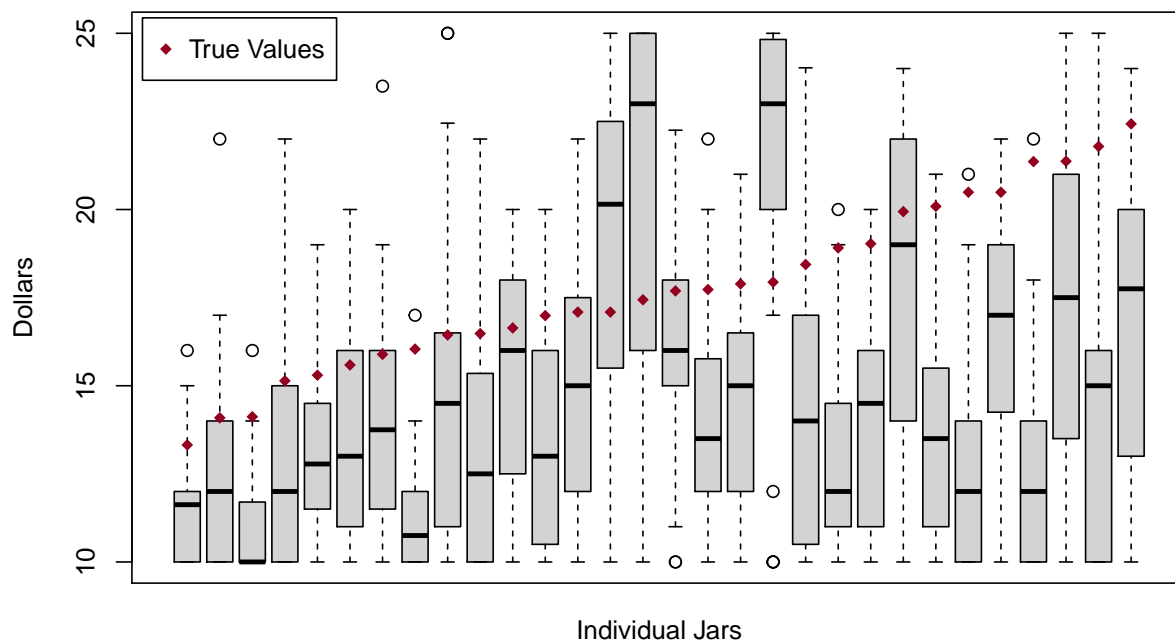
3 Results

The results are presented in three subsections. The first subsection reports the estimates of jar values from the Guess Experiment, because these serve as a reference point for estimates reported in the main experiment. The second subsection focuses on the behavior of agents in the Baseline and in the Disclosure Treatment, which is the primary focus of the paper and where our two main hypotheses are tested. The third subsection reports exploratory analysis of the behavior of principals in the Baseline and in the Disclosure Treatment.

3.1 Guess Experiment

The mean guess of jar value was \$14.61, while the mean of the true values was \$17.78. That is, the average error was -\$3.17. Figure 2 shows a boxplot of the estimates from the Guess Experiment for each jar, ordered by the actual value of the coins in the jar (not the order in which subjects in either treatment observed the jars). The \blacklozenge s show the actual value of a given jar while the thick black line gives the median guess and the gray box shows the interquartile range of guesses. In only 3 out of 30 jars did the median guess not fall below the true value. In fact, for a sizable majority of the jars the true value exceeded the 75th percentile of guesses.⁹ A sign test rejects that errors are unbiased (p -value $< .001$). This leads to Finding 1.

Figure 2: Boxplots of Incentivized Estimates and Actual Values



Note: Subject guesses for each individual jar are displayed as separate boxplots. Plots are ordered by actual value of the jar. (Subjects did not see jars in value order.)

⁹Surowiecki (2005) discusses the “wisdom of crowds,” arguing that the average value of independent assessments tends to be an accurate forecast of an unknown value (e.g., the average guess of the weight of an ox or the number of jellybeans in a jar tends to be close to the respective true values. Our subjects do not exhibit a “wisdom of crowds” for the value of coins in a jar.

Finding 1: People systematically underestimate the value of jars.

Because people so badly underestimate the true value of the jars, it is possible that someone who was deliberately inflating their estimates could still systematically report estimates below the true value. For this reason, we use the estimates from the Guess Experiment as a basis of comparison for identifying agent bias in stated estimates of value in the main experiment. While it is clear from Figure 2 that there is considerable variation across individuals with respect to their estimates of the value of a given jar, if agents in the main experiment are not systemically manipulating their estimates then on average estimates should be equal across the two experiments.

3.2 Behavior of Agents

Table 2 reports the estimates made by agents for all jars by treatment, and by whether there was a bonus to the agent if the principal chose that jar (Jar A), or if there was no bonus associated with the jar (Jar B). The average actual value of \$17.81 in Table 2 differs from the \$17.78 figure reported in the previous subsection, because most although not all jars were observed twice by agents during the main experiment and the values in Table 2 account for the frequency with which the jar was observed.

Table 2: Means by Treatment

	Baseline	Disclosure	Actual Value
Estimate Jar A	16.15	16.28	17.81
Estimate Jar B	16.36	15.88	17.81

Table 3 reports similar information to Table 2, but it is presented as deviations from the average estimates in the Guess Experiment.¹⁰ Table 3 also reports the values from (two-sided) paired t-tests and Wilcoxon rank-sum tests comparing agent's estimates when the jar is and is not bonus eligible (i.e., comparing estimates for a given image when that image is used as Jar A and Jar B, respectively). In the Baseline, the reported values for a given jar do not depend on whether the jar is Jar A or Jar B as the difference in estimates is not statistically different from zero. This result indicates that agents are not systematically favoring the bonus eligible jar in the Baseline. That is, when the conflict of interest is not disclosed there is no observed bias on the part of agents in the presence of reputation concerns. However, in the Disclosure

¹⁰Attention is restricted to cases in which the agent observed a given jar as both Jar A with a bonus payment and as Jar B without the bonus. As discussed in the previous section, a programming error meant that not all agents observed all images as both Jar A and Jar B exactly once during the experiment.

Treatment, the difference is statistically significant with agents reporting higher estimates for a jar when it is the bonus earning Jar A than when it is the non-bonus earning Jar B. This indicates that disclosure of the conflict of interest introduces bias into agent estimation despite the presence of reputation concerns.

Table 3: Deviations from Guess Treatment Estimates for Cases in which each Jar was both A and B

	Baseline	Disclosure
Estimate Jar A	1.77	2.14
Estimate Jar B	1.89	1.63
Difference	-0.11	0.52
Numb. jar pairings	300	300
t-test p-value	0.51	0.01
Wilcoxon-test p-value	0.49	0.01

Table 4: Regression Estimates for Agents' Estimates of Jars

	(1)	(2)	(3)	(4)
Constant	9.576*** (0.786)	2.965*** (0.687)		
Value	0.349*** (0.0360)		0.905*** (0.0222)	
MeanGuess		0.913*** (0.0379)		1.207*** (0.0296)
Baseline & Jar A	-0.112 (0.253)	-0.112 (0.215)	-0.112 (0.191)	-0.112 (0.191)
Disclosure & Jar B	-0.506 (0.662)	-0.513 (0.622)	-0.513 (0.534)	-0.513 (0.534)
Disclosure & Jar A	0.0112 (0.662)	0.00451 (0.622)	0.00452 (0.660)	0.00452 (0.660)
Observations	1200	1200	1200	1200
Number Unique IDs	36	36	36	36
Overall R^2	0.0675	0.285	0.343	0.343
Jar # Controls	N	N	Y	Y
Round # Controls	N	N	Y	Y
Clustering	N	N	Y	Y
Jar A - Jar B for Disclosure	0.517 (0.253)	0.517 (0.215)	0.517 (0.313)	0.517 (0.313)
$p > t $	0.0407	0.0160	0.0988	0.0988
Standard errors in parentheses		* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

To further analyze agent behavior we rely upon the following regression equation:

$$\hat{v}_{ijt} = \beta_0 + \beta_1 * Value_{jt} + \beta_2 * Baseline\&JarA_j + \beta_3 * Disclosure\&JarA_j + \beta_4 * Disclosure\&JarB_j + \varepsilon_{ijt}$$

where \hat{v}_{ijt} is agent i 's reported estimate of the value of jar j in round t . $Value_{jt}$ is a variable that captures the value of the coins in the jar for which the agent is providing an estimate. For robustness, we consider both the case where Value is the actual value of the coins in the jar (using the variable *ActualValue*) and the case where Value is the mean guess of the value of the coins in the jar from the Guess Experiment (using the variable *MeanGuess*). The main independent variables of interest are the interaction variables: *Baseline & Jar A*, *Disclosure & Jar A*, and *Disclosure & Jar B*, which are all binary variables that take the value 1 if the estimate is for the stated jar in the stated condition and take the value 0 otherwise. The omitted group is *Baseline & Jar B*, which serves as a reference point.

The regression estimation for agent reports is reported in Table 4. Specifications (1) and (3) use *ActualValue* while specifications (2) and (4) use *MeanGuess*. Specifications (1) and (2) do not include controls for the specific jars or round within a block nor do they cluster errors by agent, while specifications (3) and (4) do. We report all four specifications for the sake of robustness. The coefficient estimate for *Baseline & Jar A* is not statistically significant in any specification. In fact, it is nominally negative, indicating the mean Jar A reported estimates are, if anything, less than the mean Jar B reported estimates. This pattern provides further evidence that in the absence of disclosure agents do not provide self-serving biased estimates systematically favor Jar A. However, as shown in the lower panel, which reports the estimated difference between β_3 and β_4 , in the Disclosure Treatment agents report that a jar is worth 51.7¢ more when it is Jar A than when it is Jar B. In all four specifications, this difference is positive and at least marginally statistically significant. Thus, when the conflict of interest is disclosed to principals then agents do provide self-serving estimates of jar value. Together, the evidence in Table 3 and Table 4 support Finding 2.

Finding 2A: In the absence of disclosure, agents do not exhibit bias when there are reputation concerns.

Finding 2B: In the presence of reputation concerns, disclosure of agents' conflicts of interest leads to biased and self-serving behavior.

In terms of the model by Levitt and List (2007) discussed in the previous section, the observed behavior

indicates that agents believe disclosure creates a moral license to be self-serving and will reduce the scrutiny given to agent’s selfish action.

3.3 Behavior of Principals

Principals make three sequential decisions each round: selecting an agent, choosing a jar based on the selected agent’s estimates, and rating the agent. In this subsection we analyze these three activities in turn.

Selecting an Agent

To examine how reputation impacts a principal’s selection of an agent, we estimate the following probit model:

$$Agent2_{it} = \Phi(\beta_0 + \beta_1 * StarsDiff_{it} + \beta_2 * Disclosure_i * StarsDiff_{it} + \varepsilon_{ijt})$$

where $Agent2_{it}$ takes the value 1 if principal i chose Agent 2 in round t and the value 0 if Agent 1 was chosen. The independent variable, $StarsDiff$, is the difference in the number of stars each agent has (i.e., Agent 2’s rating - Agent 1’s rating) for the two agents in the principal’s group in the given round. $StarsDiff$ is interacted with a binary variable for the Disclosure Treatment to allow for the rating differential to matter differentially to principals across treatments. The regression clusters standard errors at the principal level and includes a random effect for each principal.

Table 5 reports marginal effects from the estimation. Specifications (1) and (2) differ in that specification (2) includes controls for the specific round within the block while specification (1) does not. The estimation shows that each additional star in an agent’s rating over and above the rating of the other agent increases the likelihood of the higher-rated agent being selected by about 32%. Interestingly, the coefficient estimate for the interaction term is indistinguishable from zero, meaning that principals do not evaluate reputations differentially across treatments. That principals are more likely to select the agent with the higher rating indicates that reputation does matter in this setting and that agents are under pressure to maintain a high rating relative to the other agents. This is stated as Finding 3.

Finding 3: Principals rely on the rating system when selecting an agent, and thus agents face reputation concerns in this setting. However, the importance of reputation does not vary with disclosure of the agent’s conflict of interest.

Table 5: Estimated Marginal Effects of Likelihood of Choosing Agent 2

	(1)	(2)
Stars Agent 2 - Stars Agent 1	0.318*** (0.044)	0.318*** (0.043)
Disclosure * (Stars Agent 2 - Stars Agent 1)	-0.000 (0.087)	0.000 (0.086)
Observations	900	900
Round # Controls	N	Y
Log Psuedolikelihood	-349.178	-346.215
Standard errors in parentheses	* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

Choosing a Jar

Similar to the approach we use for identifying which agent a principal selects, we rely on a probit model to determine what influences the jar a principal selects. Specifically, we rely upon the following specification:

$$JarB_{it} = \Phi(\beta_0 + \beta_1 * EstimateDiff + \beta_2 * Disclosure_i + \beta_3 * Disclosure_i * EstimateDiff_{it} + \varepsilon_{it})$$

where $JarB_{it}$ indicates principal i chose Jar B in round t . The independent variable of interest is $EstimateDiff$, which is the difference in the selected agent's estimate of Jar A minus the selected agent's estimate of Jar B. The regression includes a random effect for each principal and clusters standard errors by principal. Table 6 reports estimated marginal effects from the probit regression. In specification (1) it is assumed that there is no difference in jar selection between treatments, while specification (2) allows for the difference in jar selection to vary between treatments. The $Disclosure$ variable tests to see if the variation is significant. Specification (3) allows for a shift in jar selection due to the treatment. It also includes an interaction term between the treatment and $EstimateDiff$.

Table 6: Estimated Marginal Effects of Likelihood of Choosing Jar B

	(1)	(2)	(3)
Estimate Jar A - Estimate Jar B	-0.078*** (0.006)	-0.078*** (0.006)	-0.085*** (0.010)
Disclosure		-0.106* (0.041)	-0.101* (0.040)
Disclosure * (Est. Jar A - Est. Jar B)			0.016 (0.020)
Observations	1044	1044	1044
Log Psuedolikelihood	-496.738	-493.641	-492.104
Base Rate	0.384	0.463	0.462
Standard errors in parentheses	* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

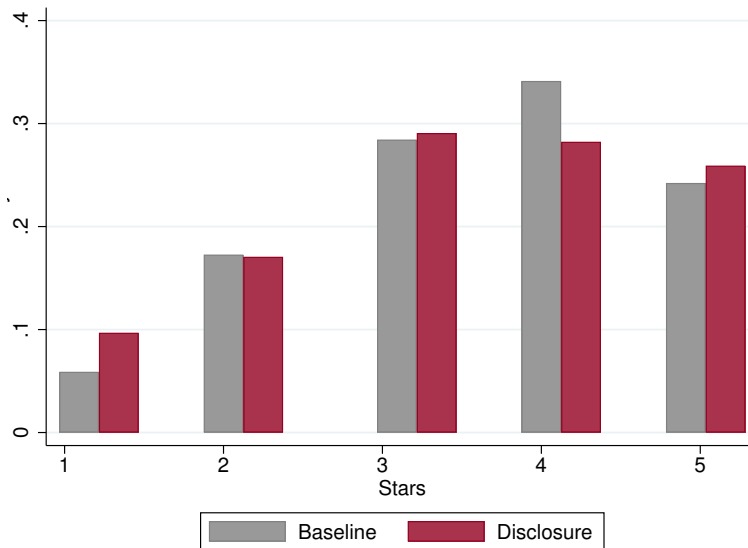
The interpretation of the marginal effect of $EstimateDiff$ is that for every dollar that the estimate of Jar A exceeds Jar B there is a 8% decrease in the chance that Jar B is picked. The negative sign on this coefficient (in all specifications) is what one would expect if principals believe agent estimations convey useful information. From specifications (2) and (3), principals in the Disclosure Treatment are actually *less* likely to choose Jar B by 12% as compared to the Baseline, *ceteris paribus*. This effect is the opposite of what one would observe if principals were wary of choosing Jar A in the Disclosure Treatment, but it is consistent with principals not fully appreciating the implications of the agent’s conflict of interest and having a desire to help the agents earn a larger profit. Specification (3) reveals that the impact of differences in the reported estimated values of the jars does not vary with treatment. This leads to Finding 4.

Finding 4: Subjects directly rely on the agents’ estimates of jar value to determine which option to select in both treatments. However, Disclosure actually increases the likelihood that the principal will select the option that benefits the agent *ceteris paribus*.

Rating the Agent

Figure 3 plots how often each star rating was assigned by treatment. The mean number of stars in the Disclosure Treatment (3.397) was slightly lower than the mean in the Baseline (3.487), but the difference is not statistically significant (p -value = 0.226).

Figure 3: Histogram of Stars (Ratings) of Agents



To understand how agent performance impacts the rating a principal gives an agent after observing the true value of the selected jar and the independent noisy signal of the value of the other jar, we rely on the two following specifications. The first specification classifies jars based on whether the agent had a conflict of interest with the jar or not (i.e., Jar A versus Jar B).

$$\begin{aligned} Stars_{it} = & \beta_0 + \beta_1 * AccurateDirection_{it} + \beta_2 * OverEstJarA_{it} + \beta_3 * UnderEstJarA_{it} \\ & + \beta_4 * OverEstJarB_{it} + \beta_5 * UnderEstJarB_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

where $Stars_{it}$ is the number of stars principal i assigned the selected agent in round t . $AccurateDirection$ is a binary variable indicating that the jar the agent reported as having the highest value also had the highest value based upon the information subsequently revealed to the principal. That is, $AccurateDirection$ takes the value 1 if the agent provided guidance to the principal that was in the “Accurate Direction” and is 0 otherwise. The remaining variables pertain to the difference between the agent’s estimate of a jar’s value and the subsequent information received by the principal. $OverEstJarX$ is the amount the principal believes the agent overestimated the value of Jar X while $UnderEstJarX$ is the amount the principal believes the agent underestimated the value of Jar X.

The second specification classifies jars based on whether the principal selected the jar or not.

$$\begin{aligned} Stars_{it} = & \beta_0 + \beta_1 * AccurateDirection_{it} + \beta_2 * OverEstPick_{it} + \beta_3 * UnderEstPick_{it} \\ & + \beta_4 * OverEstOther_{it} + \beta_5 * UnderEstOther_{it} + \varepsilon_{it} \end{aligned} \quad (2)$$

where, similarly to Equation 1, $OverEstPick$ ($UnderEstPick$, $OverEstOther$, $UnderEstOther$) denotes the amount by which the principal believes the agent over- (under-, over-, under-) estimated the value of the selected (selected, not selected, not selected) jar, respectively. This approach allows for the possibility that principals view errors asymmetrically. For both equations 1 and 2, we report 3 estimations. The first is just the basic specification given above. The second specification includes $Disclosure$, a binary variable for the Disclosure Treatment, as well as the interaction of $Disclosure$ and $AccurateDirection$. The third specification adds interaction terms for the type of error an agent made and the treatment to allow for the possibility that overestimation and underestimation are viewed differently between treatments.

Table 7 reports regression estimates using Equation 1, and Table 8 reports regression estimates using Equation 2. In all three specifications in both tables, the coefficient on $AccurateDirection$ is positive and

statistically significant, meaning that principals rate agents higher when the agent’s rank order Jars in a manner consistent with the independent information the principal receives. From all three specifications in both Tables 7 and 8 it is clear that agents are penalized for errors in their estimation. Specifications (2) and (3) in both tables indicate that ratings are not systematically different across treatments (*AccurateDirection* & *Disclousre* is not significant in any specification). The lower panel of both tables provides the p -values for testing for symmetry among the types of errors that an agent could make in her estimations. For each case there are six possible tests since there are four coefficients for over- and underestimation.¹¹

From Table 7 there is no evidence that overestimation of Jar A is treated differently than overestimation of Jar B, nor is underestimation viewed differently between jars. However, underestimation of a jar is viewed more negatively than overestimation of the same jar, although this difference is not always statistically significant across specifications and treatments. Interestingly, greater concern for underestimation as compared to overestimation holds across jars as well, at least for the Baseline. However, in the Disclosure Treatment when the principal knows the agent has an incentive to make Jar A appear more attractive, this cross-jar asymmetry disappears. That is, in the Disclosure Treatment, the principal views overestimating Jar A the same as underestimating Jar B as these two errors both make Jar A appear more attractive.

Unsurprisingly, Table 8 shows that overestimation of the jar selected is viewed more negatively than underestimation of the jar selected. Additionally, overestimation of the jar selected is viewed more negatively than overestimation of the jar not selected, which is intuitive. Overall, errors regarding the jar selected are viewed more negatively than oppositely signed errors for the non-selected jar. Thus, overestimation of the selected jar leads to a greater reduction in rating than does underestimating the value of the non-selected jar even though both errors have the same impact on assessing the difference in value between the two jars. But this asymmetry is limited to the Baseline as indicated by the tests of specification (3).

The results reported in Tables 7 and 8 support the final finding.

Finding 5A: Principals reward agents with higher ratings when the agent appears to correctly identify the best option and punish agents with lower ratings for misestimation.

¹¹For specification (3) in Tables 7 and 8 there are six tests for each treatment since the impact of errors is allowed to vary by treatment.

Table 7: Estimated Impacts on Ratings Given to Agent using Jar Identity

	(1)	(2)	(3)
AccuateDirection	0.555*** (0.134)	0.506*** (0.114)	0.486*** (0.115)
OverEstJarA	-0.094*** (0.022)	-0.094*** (0.022)	-0.127*** (0.024)
UnderEstJarA	-0.175*** (0.024)	-0.176*** (0.024)	-0.208*** (0.022)
OverEstJarB	-0.117*** (0.023)	-0.117*** (0.024)	-0.095*** (0.028)
UnderEstJarB	-0.156*** (0.030)	-0.155*** (0.030)	-0.210*** (0.029)
Disclosure		-0.037 (0.216)	-0.251 (0.305)
AccuateDirection & Disclosure		0.097 (0.266)	0.137 (0.265)
OverEstJarA & Disclosure			0.068 (0.044)
UnderEstJarA & Disclosure			0.048 (0.045)
OverEstJarB & Disclosure			-0.044 (0.046)
UnderEstJarB & Disclosure			0.103* (0.056)
Constant	3.962*** (0.159)	3.982*** (0.168)	4.099*** (0.178)
Observations	1,044	1,044	1,044
Number of Unique IDs	36	36	36
Tests of symmetry			
OverEstJarA = UnderEstJarA	0.000	0.000	0.001
OverEstJarB = UnderEstJarB	0.131	0.153	0.000
OverEstJarA = OverEstJarB	0.496	0.500	0.341
UnderEstJarA = UnderEstJarB	0.633	0.608	0.936
OverEstJarA = UnderEstJarB	0.077	0.083	0.015
UnderEstJarA = OverEstJarB	0.091	0.086	0.000
OverEstJarA + OverEstJarADisc = UnderEstJarA + UnderEstJarADisc			0.005
OverEstJarB + OverEstJarBDisc = UnderEstJarB + UnderEstJarBDisc			0.449
OverEstJarA + OverEstJarADisc = OverEstJarB + OverEstJarBDisc			0.170
UnderEstJarA + UnderEstJarADisc = UnderEstJarB + UnderEstJarBDisc			0.465
OverEstJarA + OverEstJarADisc = UnderEstJarB + UnderEstJarBDisc			0.437
UnderEstJarA + UnderEstJarADisc = OverEstJarB + OverEstJarBDisc			0.715

The results in the first four rows for specification (3) examine symmetry in the baseline and the last four test rows of specification test for symmetry in Disclosure.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Estimated Impacts on Ratings Given to Agent using Jar Selection

	(1)	(2)	(3)
AccuateDirection	0.517*** (0.113)	0.436*** (0.112)	0.501*** (0.111)
OverEstPick	-0.244*** (0.027)	-0.246*** (0.027)	-0.274*** (0.031)
UnderEstPick	-0.108*** (0.031)	-0.108*** (0.031)	-0.161*** (0.033)
OverEstOther	-0.050** (0.024)	-0.047* (0.026)	-0.087*** (0.024)
UnderEstOther	-0.106*** (0.022)	-0.107*** (0.023)	-0.068*** (0.017)
Disclosure		-0.098 (0.218)	-0.127 (0.272)
AccuateDirection & Disclosure		0.159 (0.263)	0.045 (0.226)
OverEstPick & Disclosure			0.058 (0.053)
UnderEstPick & Disclosure			0.110* (0.062)
OverEstOther & Disclosure			0.056 (0.047)
UnderEstOther & Disclosure			-0.081* (0.043)
Constant	4.011*** (0.139)	4.064*** (0.166)	4.068*** (0.179)
Observations	1,044	1,044	1,044
Number of Unique IDs	36	36	36
OverEstPick = UnderEstPick	0.000	0.000	0.000
OverEstOther = UnderEstOther	0.0630	0.0680	0.476
OverEstPick = OverEstOther	0.000	0.000	0.000
UnderEstPick = UnderEstOther	0.958	0.976	0.006
OverEstPick = UnderEstOther	0.000	0.000	0.000
OverEstOther = UnderEstPick	0.100	0.083	0.080
OverEstPick + OverEstPickDisc = UnderEstPick + UnderEstPickDisc			0.001
OverEstOther + OverEstOtherDisc = UnderEstOther + UnderEstOtherDisc			0.030
OverEstPick + OverEstPickDisc = OverEstOther + OverEstOtherDisc			0.008
UnderEstPick + UnderEstPickDisc = UnderEstOther + UnderEstOtherDisc			0.220
OverEstPick + OverEstPickDisc = UnderEstOther + UnderEstOtherDisc			0.256
OverEstOther + OverEstOtherDisc = UnderEstPick + UnderEstPickDisc			0.730

The results in the first four rows for specification (3) examine symmetry in the baseline and the last four test rows of specification test for symmetry in Disclosure.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finding 5B: The reduction in rating tends to be greater for underestimation than overestimation of a given jar; however, with Disclosure principals view overestimating one jar and underestimating the other jar as comparable. After selecting a jar, principals are more strongly concerned with errors regarding the selected jar; but, with Disclosure principals view overestimation of the selected jar as being comparable to underestimation of the other jar.

4 Choice Treatment

The two treatments in the preceding section forced agents to have a conflict of interest. However, in practice doctors are not required to accept gifts from pharmaceutical companies nor do lawyers have to take on specific clients. To assess how the endogeneity of the conflict of interest might impact the behavior of principals and agents, we conducted an additional treatment, which we refer to as the Choice treatment.¹² In Choice, agents choose whether or not to receive the 50¢ bonus if a principal in their group selects them as an agent and then selects Jar A. Agents make their choice regarding being eligible for the bonus between Stage 0 and Stage 1 in Table 1, that is before the agents observe the relevant jars. At Stage 2, principals in Choice observe the agents' choices regarding the bonus payment as well as the agents' star ratings. Otherwise, Choice followed the same procedures as Baseline and Disclosure. A total of 3 sessions were conducted involving 36 additional subjects. The average earnings among these subjects was \$24.56, including the \$7 participation payment.

Ultimately, agents overwhelmingly opted to be eligible for the bonus, resulting in a conflict of interest 73% of the time. All agents opt for the bonus in at least one round. One agent selects the bonus in only one round. Three agents take the option in all rounds. There is also some evidence that fewer agents opt to be bonus eligible in later rounds than in earlier rounds. Because so many agents opt to have a conflict of interest, it is unsurprising that behavior in Choice is quite similar to that observed in Disclosure. The remainder of this section reports the results of the Choice treatment in parallel to those previously reported for Baseline and Disclosure.

Table 9 is similar to Table 3 and reports the difference between an agent's stated estimate and the mean estimate of the same jar's value from the Guess treatment. Table 9 is limited to the set of jars an individual agent saw as both Jar A and Jar B and having made the same choice regarding the bonus both

¹²This treatment was conducted at the same time as Baseline and Disclosure.

times. When the agent does not have a conflict of interest, there is virtually no difference in the estimated value based on the jar being labeled Jar A or Jar B. However, when the agent was eligible for the bonus the jar’s estimated value was substantially greater when it was labeled Jar A. This difference, though quite large, is not statistically significant, but this is due to the small number of observations, in which an agent saw the same jar twice and made the same bonus decision in both instances.

Table 9: Deviations from Guess Treatment Estimates for Cases in which each Jar was both A and B

	No Bonus	Bonus
Estimate Jar A	1.54	0.79
Estimate Jar B	1.96	0.43
Difference	-0.43	0.36
Number of jar pairings	78	174
t-test p-value	0.22	0.21
Wilcoxon-test p-value	0.16	0.37

Table 10 is similar to Table 4 and reports regression results for the estimated values the agents provide to the principals. The coefficient on No Bonus & Jar A indicates that when the agent does not have a conflict of interest the estimated value does not depend on the jar’s label. However, the statistical tests reported at the bottom of Table 10 indicate that when agents have a conflict of interest they estimate the jar’s value to be greater if it is labeled Jar A.

We now turn to the behavior of the principals. Table 11 reports the marginal effects on the probability the principal selects Agent 2 and is similar to Table 5. The results indicate that the number of stars an agent has influences the principal’s selection with higher rated agents being more likely to be selected. The results also reveal that an agent’s decision to be eligible for the bonus has no bearing on the principal’s selection decision.

The above analysis shows that principals do not avoid agents with conflicts of interest. Table 12 shows that principals do not treat the recommendations from agents who are eligible for the bonus differently than they treat recommendations from agents who do not have a conflict of interest. Specifically, this is shown by the lack of significance for the interaction term in specification (3). As was revealed in Table 6, Table 12 also indicates principals tend to favor Jar A when selecting it will earn the agent a bonus. In fact, Jar A is 17% more likely to be selected when the agent *has* a conflict of interest.

Table 10: Regression Estimates for Agents' Estimates of Jars in Choice Treatment

	(1)	(2)	(3)	(4)
Constant	7.921*** (0.899)	2.219*** (0.668)	-126.6*** (11.56)	2.404* (1.213)
Value	0.465*** (0.0445)		8.531*** (0.695)	
MeanGuess		0.950*** (0.0376)		0.888*** (0.0724)
No Bonus & Jar A	0.00619 (0.411)	-0.202 (0.339)	-0.251 (0.347)	-0.251 (0.347)
Bonus Eligible & Jar B	-0.715 (0.411)	-0.519 (0.346)	-0.761* (0.339)	-0.761* (0.339)
Bonus Eligible & Jar A	-0.230 (0.411)	0.0439 (0.346)	-0.179 (0.343)	-0.179 (0.343)
Observations	1044	1044	1044	1044
Overall R^2	0.0976	0.359	0.441	0.441
Number Unique IDs	18	18	18	18
Jar # Controls	N	N	Y	Y
Round # Controls	N	N	Y	Y
Clustering	N	N	Y	Y
Jar A - Jar B if Bonus Eligible	0.485 (0.251)	0.563 (0.207)	0.582 (0.196)	0.582 (0.196)
$p > t $	0.0535	0.00663	0.00307	0.00307
Standard errors in parentheses			* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

Table 11: Estimated Marginal Effects of Likelihood of Choosing Agent 2

	(1)	(2)
Stars Agent 2 - Stars Agent 1	0.273*** (0.020)	0.272*** (0.020)
Bonus Jar A Agent 2 - Bonus Jar A Agent 1	-0.003 (0.038)	-0.010 (0.039)
Observations	450	450
Round # Controls	N	Y
Log Psuedolikelihood	-133.829	-128.736
Standard errors in parentheses		* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Estimated Marginal Effects of Likelihood of Choosing Jar B in Choice Treatment

	(1)	(2)	(3)
Estimate Jar A - Estimate Jar B	-0.056*** (0.009)	-0.054*** (0.009)	-0.074*** (0.018)
Bonus for Jar A		-0.173*** (0.042)	-0.168*** (0.047)
Bonus for Jar A * (Est. Jar A - Est. Jar B)			0.026 (0.020)
Observations	522	522	522
Log Psuedolikelihood	-292.462	-283.443	-281.451
Base Rate	0.388	0.543	0.541
Standard errors in parentheses	* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

Table 13: Estimated Impacts on Ratings Given to Agent using Jar Identity

	(1)	(2)	(3)
AccurateDirection	0.258 (0.164)	0.518** (0.206)	0.526*** (0.203)
OverEstJarA	-0.090*** (0.033)	-0.090*** (0.034)	-0.031 (0.040)
UnderEstJarA	-0.126** (0.052)	-0.124** (0.052)	-0.079 (0.068)
OverEstJarB	-0.103*** (0.021)	-0.101*** (0.019)	-0.104*** (0.031)
UnderEstJarB	-0.188*** (0.035)	-0.181*** (0.035)	-0.185* (0.094)
Bonus for Jar A		0.007 (0.140)	0.250 (0.180)
OverEstJarA & Bonus for Jar A			-0.082** (0.033)
UnderEstJarA & Bonus for Jar A			-0.061 (0.050)
OverEstJarB & Bonus for Jar A			0.006 (0.036)
UnderEstJarB & Bonus for Jar A			0.006 (0.103)
AccurateDirection & Bonus for Jar A		-0.368** (0.177)	-0.372** (0.182)
Constant	4.235*** (0.231)	4.219*** (0.297)	4.040*** (0.265)
Observations	522	522	522
Number of Unique IDs	18	18	18
Overall R^2	0.162	0.173	0.182
OverEstJarA = UnderEstJarA	0.250	0.267	0.306
OverEstJarB = UnderEstJarB	0.00300	0.00900	0.400
OverEstJarA = OverEstJarB	0.684	0.716	0.187
UnderEstJarA = UnderEstJarB	0.345	0.410	0.472
OverEstJarA = UnderEstJarB	0.0230	0.0560	0.153
UnderEstJarA = OverEstJarB	0.631	0.658	0.743
OverEstJarA + OverEstJarAPayA = UnderEstJarA + UnderEstJarAPayA			0.458
OverEstJarB + OverEstJarBPayA = UnderEstJarB + UnderEstJarBPayA			0.0110
OverEstJarA + OverEstJarAPayA = OverEstJarB + OverEstJarBPayA			0.668
UnderEstJarA + UnderEstJarAPayA = UnderEstJarB + UnderEstJarBPayA			0.521
OverEstJarA + OverEstJarAPayA = UnderEstJarB + UnderEstJarBPayA			0.104
UnderEstJarA + UnderEstJarAPayA = OverEstJarB + OverEstJarBPayA			0.381

The results in the first four rows for specification (3) examine symmetry in not selecting a bonus and the last four test rows of specification test for symmetry in selecting a bonus for Jar A.

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Finally, we report Table 13 to identify how the rating principals give agents depends on whether the agent chose to have a conflict of interest. This analysis is akin to that reported in Table 7. The results indicate that having a conflict of interest is not, on its own, viewed as a reason to rate an agent lower. However, principals do not reward agents with a conflict of interest as much for accurately identifying the jar with the greater value as they do agents without such a conflict. Additionally, while misestimation of the value of Jar B or underestimation of Jar A has a similar negative impact on a agent’s rating regardless of whether the agent has a conflict of interest, agents with a conflict of interest are judged more severely for overestimating the value of Jar A.

5 Discussion

Conventional wisdom suggests that an agent’s conflict of interest should be disclosed to principals. However, such a policy can prove harmful if disclosure creates a moral license that emboldens agents and encourages them to act in self-serving ways, especially if the magnitude of this effect is not fully appreciated by principals. This negative effect was reported in Cain et al. (2005). Our paper extends the basic structure of Cain et al. (2005) to a repeated interaction situation in which agents have reputation concerns. We further extend the design to endogenize the agent’s choice of whether to have conflict of interest. The goal of our paper is three-fold. First, we seek to understand if the disciplining effect of maintaining a reputation can offset the incentives created by a conflict of interest. Second, we examine the effect of disclosure in a setting where the agent has a reputation concern. Third, we investigate how the agent’s choices to have a conflict of interest impacts principal–agent relationship with disclosure.

In our experimental task, principals rated agents based on the agent’s performance estimating the value of options available to the principal. In turn, principals could select agents based upon those ratings. Agents had a conflict of interest in that they received a direct benefit from increasing the principals belief about the relative value of a particular option. In the absence of disclosure, agents did not provide self-serving biased estimates. This indicates that reputation concerns alone can be enough to offset conflicts of interest. This is in line with Koch and Schmidt (2010) who found fixed matching of principals and agents reduced bias in comparison to a re-matching protocol. However, when disclosure of the conflict of interest was required, we did observe self-serving behavior on the part of agents. Somewhat surprisingly, principals did not discount agents behavior when the conflict of interest was disclosed, in contrast to Cain et al. (2005) but similar to Cain et al. (2011) who, like our design, had agent payoffs tied to principal earnings. The manipulation of

information by agents that we observe involves a mix of inflating estimates of the option that provided a benefit to the agent and deflating the estimate of the other option. Thus, we find that the counterintuitive result of Cain et al. (2005) that disclosure can exacerbate a conflict of interest holds even in the presence of reputation concerns. Additionally, we find that principals do not avoid agents who opt to have conflicts of interest.

While not the main focus of our study, the observed behavior does provide some additional insights. First, we find that misestimation of an option, whether it is ultimately the one selected or not, leads to a reduction in the rating a principal assigns to an agent. However, in the Baseline Treatment overestimating the benefit from a selected option leads to a greater reduction in the rating than underestimating the value of an option not selected, despite these errors having similar implications for the principal. But in the Disclosure Treatment principals view the two errors similarly. Second, we find little evidence that with disclosure principals punish agents for self-serving estimates. In particular, there are no differences in how over- or underestimation of a particular option is treated between Baseline and Disclosure. The one case where we observe punishment for self-serving behavior is in the Choice treatment where the agent's conflict is endogenous. Finally, we note that our subjects, like those in Cain et al. (2005), were unable to accurately guess the value of the options, which were jars of coins, in a separate experiment used to calibrate unbiased expectations of those values. Instead, average estimates were systematically below the actual values, contrary to the arguments in Surowiecki (2005).

It is worth noting that the success of reputation concerns in deterring self-serving behavior by agents may be dependent upon two key features of our setting. First, principals in our study were effectively consuming a credence good since they could not verify the quality of their choice. However, the principals did receive a noisy signal of the quality. Second, the size of the conflict of interest was relatively small, in that a majority of the agent's earnings were from being selected by a principal rather than having the principal select a particular choice. Whether a conflict of interest would lead to self-serving behavior when reputation concerns are present but either or both of these features is relaxed remains an important question. Similarly, the negative effects of disclosure that we observe may or may not hold as these two factors are relaxed. It is certainly possible that principals who know that agents have a substantial conflict of interest or who have weaker signals of agent performance may behave differently. We hope that our work will spark interest in these important avenues for future research.

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Appendices

A.1 Instructions

The experiment instructions were computerized, but subjects were informed that they could raise their hand if they had any questions. Screenshots of instructions are below.

Guess Treatment

The Guess Treatment had two instruction screens.

Pay





Welcome and thank you for participating in this experiment! Your task is to view photos of jar containing coins and then correctly guess the value of the coins in the jar.

There will be 30 rounds. Each round your lab earnings equals $\$25 - \$2 * (\text{Actual value} - \text{Your guess})^2$, if your earnings would be less than zero for a round, then they will be zero. This equation may look complicated but what it means is that you should provide the most accurate guess you can in order to earn the most money that you can. The more accurate your prediction the more you will earn. Your final payment in \$US will be the AVERAGE of your lab earnings across all rounds plus the show-up payment.

Next

The Task

All the pictures in the study are of jars containing between \$10.00 and \$25.00. To help everyone understand the task, here are some example pictures. Notice, that the height of the coins is not the only factor to consider when estimating value. The composition of the coins must also be considered. For the examples below, the two jars on the left are only about half full, while one contains \$16.00 and the \$22.00. However, the two on the right are nearly filled to the top, and also \$16.00 and \$22.00.

\$16.00	\$22.00	\$16.00	\$22.00
			

Next

Main Treatments

The main treatments had four instruction screens with conditional text. Annotation shows what text was conditional on treatment.

Instructions

Welcome and thank you for participating in this experiment! There are two roles in the experiment, '*Investors*' and '*Experts*'. You will be assigned one of these roles and remain in that role for the entire experiment.

There will be **four blocks**, each which will last a random number of rounds. Each block lasts at least 5 rounds. Every round after the 5th round there is 25% chance the block will end.

Next

Steps

Each round you will be assigned to a group, consisting of two *Investors* and two *Experts*. Your group is randomly determined each round so you will be interacting with different people over the course of the block and across blocks although you may encounter the same people multiple times.

1. Each *Investor* picks an *Expert* for the round (except the first round when they are randomly assigned).
2. Each round, *Experts* see photos of two jars, A and B, and estimate the value of the coins in each jar.
3. *Investors* then pick an *Expert* and see that *Expert*'s estimates for both jars, but will not see the photos or the estimates of the *Expert* not picked.
4. The *Investor* then picks a jar and learns the exact amount in the chosen jar. The *Investor* will also get a computer generated signal about the amount in the jar that was not selected. The signal is the actual amount in the jar that was not chosen plus a random number (between -\$2 and +\$2).
5. The *Investor* then rates the chosen *Expert*
6. At the start of every round after the first round, *Investors* will be able to see the ratings of the two *Experts* in the group.

Next

Pay

The *Investors*'s earning for a round equals the actual amount in the Jar. At the end of the experiment, one round will be randomly selected and the amount in Jar selected by the *Investors* that period will be the payoff the *Investors* receives.

An *Expert*'s earnings depend in part on the number of *Investors* who pick that *Expert*. Every round an *Expert* earns \$0.75 for each *Investor* who picks that *Expert*. **In addition, an *Expert* earns an extra \$0.50 for each of those *Investors* who goes on to pick Jar A.** Only in Disclosure Treatment





At the end of the experiment, two blocks will be randomly selected for each *Expert*. *Experts* will receive all money earned in all periods in those blocks.

In the Choice Treatment, the text was "In addition, *Experts* have the option of earning an extra \$0.50 for each of those *Investors* who goes on to pick Jar A. *Investors* will be able to see if the *Experts* they are selecting from in a given round have taken this option."

Next

The Task

All the pictures in the study are of jars containing between \$10.00 and \$25.00. To help everyone understand the task, here are some example pictures. Notice, that the height of the coins is not the only factor to consider when estimating value. The composition of the coins must also be considered. For the examples below, the two jars on the left are only about half full, while one contains \$16.00 and the \$22.00. However, the two on the right are nearly filled to the top, and also \$16.00 and \$22.00.

\$16.00	\$22.00	\$16.00	\$22.00
			

Next

A.2 Programming Error

In Round 1, agents saw Jars 1 and 2; for Agent 1 Jar 1 was Jar A and Jar 2 was Jar B, vice versa for Agent 2. In Round 2, agents saw Jars 3 and 4, assigned to A and B as above. Rounds continued like this until Round 15. In Round 15, agents saw Jars 1 and 2 a second time, with the assignment to A and B reversed. For Agent 2 Jar 1 was Jar A and Jar 2 was Jar B. This reversal occurred in Rounds 16 - 28 as well with each round being a swap of the round 14 rounds earlier. However, in round 29, the last given the random termination, Agents saw Jar 29 and Jar 30, which they had not seen before. Because of the odd number of rounds not every jar was observed twice.

Had every subject always been Agent 1 or always been Agent 2, every agent would have two estimates for each jar (1 to 28); one when the jar was Jar A and one when it was Jar B. However, there was an error in the logic of our program. A subject who was Agent 1 in the first half (e.g., Round 1) of the experiment could be Agent 2 14 rounds later (e.g., Round 15). As a result, while we have two estimates for each jar from 1-28 from each agent, for some agents some jars were estimates twice as Jar A and for others the jars were estimated twice as Jar B. For the analysis in the body of the paper, we only included estimates for which there were Jar A and Jar B estimates for the same jar by the same agent. Table A.1 reports estimates from repeating the regressions in Table 4 including all the estimates. The results are qualitatively similar. In the Baseline, guesses for the value of Jar B are larger than those for Jar A, but not by a statistically significant margin. In contrast, in the Disclosure Treatment, the guesses for the value of Jar A were 41¢ higher than those for Jar B.

A.3 Ordered Probit Regressions

Tables A.2 through A.4 present results from analysis complementary to that reported in Table 7. However, rather than treating the number of stars awarded to an agent as a continuous variable, this supplementary analysis treats the ratings as discrete ranked options and thus uses ordered probit regressions. Each table reports the marginal effects of the probit regression in parallel to one of the specifications in Table 8. For these tables, each column is the effect from a single independent variable and each row is the change in the likelihood of an agent receiving that number of stars for a one unit change in the variable. The results are consistent with those from Table 8.

Table A.1: KEEP ALL Regression Estimates for Agents' Estimates of Jars

VARIABLES	(1)	(2)	(3)	(4)
Constant	9.254*** (0.655)	3.544*** (0.529)	-131.457*** (12.882)	3.011** (1.279)
Value	0.399*** (0.029)		8.889*** (0.770)	
MeanGuess		0.880*** (0.024)		0.926*** (0.080)
Baselime & JarA	-0.205 (0.200)	-0.205 (0.163)	-0.205 (0.175)	-0.205 (0.175)
Disclosure & Jar A	-0.075 (0.560)	-0.075 (0.554)	-0.075 (0.573)	-0.075 (0.573)
Disclosure & Jar B	-0.480 (0.560)	-0.480 (0.554)	-0.480 (0.515)	-0.480 (0.515)
Observations	2,088	2,088	2,088	2,088
Number of Unique IDs	36	36	36	36
Overall R2	0.0701	0.318	0.356	0.356
Jar # Controls	N	N	Y	Y
Round # Controls	N	N	Y	Y
Clustering	N	N	Y	Y
JarA - JarB for Disclosure	0.405	0.405	0.405	0.405
SE	0.200	0.163	0.223	0.223
P> t	0.043	0.013	0.069	0.069
Standard errors in parentheses		*** p<0.01, ** p<0.05, * p<0.1		

Table A.2: Order Probit of Impacts on Rating given to Agent, Jar A vs. B, Model 1

VARIABLES	(1) DIRECTACC	(2) OverEstJarA	(3) UnderEstJarA	(4) OverEstJarB	(5) UnderEstJarB
1 Star	-0.0640*** (0.0189)	0.0106*** (0.00312)	0.0192*** (0.00391)	0.0131*** (0.00302)	0.0176*** (0.00387)
2 Stars	-0.0785*** (0.0179)	0.0130*** (0.00342)	0.0236*** (0.00377)	0.0160*** (0.00344)	0.0216*** (0.00467)
3 Stars	-0.0512*** (0.0125)	0.00845*** (0.00215)	0.0154*** (0.00346)	0.0105*** (0.00319)	0.0141*** (0.00402)
4 Stars	0.0440*** (0.0109)	-0.00727*** (0.00231)	-0.0132*** (0.00267)	-0.00900*** (0.00230)	-0.0121*** (0.00324)
5 Stars	0.150*** (0.0342)	-0.0247*** (0.00560)	-0.0449*** (0.00660)	-0.0306*** (0.00645)	-0.0412*** (0.00793)
Observations	1,044	1,044	1,044	1,044	1,044
Standard errors in parentheses		*** p<0.01, ** p<0.05, * p<0.1			

Table A.3: Order Probit of Impacts on Rating given to Agent, Jar A vs. B, Model 2

VARIABLES	(1) DIRECTACC	(2) OverEstJarA	(3) UnderEstJarA	(4) OverEstJarB	(5) UnderEstJarB	(6) DISC	(7) DirectAccDISC
1 Star	-0.0603*** (0.0143)	0.0106*** (0.00311)	0.0193*** (0.00394)	0.0131*** (0.00300)	0.0176*** (0.00384)	0.00277 (0.0231)	-0.00725 (0.0302)
2 Stars	-0.0741*** (0.0180)	0.0130*** (0.00333)	0.0236*** (0.00372)	0.0161*** (0.00347)	0.0216*** (0.00478)	0.00341 (0.0281)	-0.00890 (0.0365)
3 Stars	-0.0483*** (0.0132)	0.00849*** (0.00208)	0.0154*** (0.00341)	0.0105*** (0.00319)	0.0141*** (0.00406)	0.00222 (0.0184)	-0.00580 (0.0237)
4 Stars	0.0416*** (0.0116)	-0.00730*** (0.00228)	-0.0133*** (0.00267)	-0.00900*** (0.00234)	-0.0121*** (0.00331)	-0.00191 (0.0157)	0.00499 (0.0204)
5 Stars	0.141*** (0.0293)	-0.0248*** (0.00549)	-0.0451*** (0.00659)	-0.0306*** (0.00645)	-0.0411*** (0.00804)	-0.00649 (0.0538)	0.0170 (0.0700)
Observations	1,044	1,044	1,044	1,044	1,044	1,044	1,044
Standard errors in parentheses						*** p<0.01, ** p<0.05, * p<0.1	

Table A.4: Order Probit of Impacts on Rating given to Agent, Jar A vs. B, Model 3

VARIABLES	DIRECTACC	OverEstJarA	UnderEstJarA	OverEstJarB	UnderEstJarB	DISC
1 Star	-0.0582*** (0.0142)	0.0145*** (0.00364)	0.0231*** (0.00439)	0.0109*** (0.00361)	0.0239*** (0.00466)	0.0304 (0.0345)
2 Stars	-0.0715*** (0.0179)	0.0178*** (0.00391)	0.0283*** (0.00387)	0.0134*** (0.00371)	0.0294*** (0.00441)	0.0373 (0.0391)
3 Stars	-0.0468*** (0.0131)	0.0116*** (0.00268)	0.0185*** (0.00409)	0.00876*** (0.00328)	0.0192*** (0.00496)	0.0244 (0.0268)
4 Stars	0.0399*** (0.0113)	-0.00991*** (0.00283)	-0.0158*** (0.00356)	-0.00747*** (0.00247)	-0.0164*** (0.00339)	-0.0208 (0.0219)
5 Stars	0.137*** (0.0294)	-0.0339*** (0.00606)	-0.0541*** (0.00593)	-0.0256*** (0.00759)	-0.0562*** (0.00855)	-0.0712 (0.0779)
VARIABLES	DirectAccDISC	OverEstJarADisc	UnderEstJarADisc	OverEstJarBDisc	UnderEstJarBDisc	
1 Star	-0.0111 (0.0298)	-0.00789 (0.00492)	-0.00587 (0.00513)	0.00421 (0.00522)	-0.0120* (0.00655)	
2 Stars	-0.0136 (0.0355)	-0.00970 (0.00614)	-0.00722 (0.00619)	0.00517 (0.00671)	-0.0147** (0.00743)	
3 Stars	-0.00891 (0.0232)	-0.00634 (0.00419)	-0.00472 (0.00424)	0.00338 (0.00432)	-0.00963* (0.00552)	
4 Stars	0.00760 (0.0197)	0.00541 (0.00355)	0.00403 (0.00375)	-0.00288 (0.00370)	0.00822** (0.00410)	
5 Stars	0.0260 (0.0688)	0.0185 (0.0115)	0.0138 (0.0117)	-0.00987 (0.0125)	0.0281* (0.0150)	
Observations	1,044	1,044	1,044	1,044	1,044	
Standard errors in parentheses						*** p<0.01, ** p<0.05, * p<0.1

Tables A.5 through A.7 present results from analysis complementary to that reported in Table 8. However, rather than treating the number of stars awarded to an agent as a continuous variable, this supplementary analysis treats the ratings as discrete ranked options and thus uses ordered probit regressions. Each table reports the marginal effects of the probit regression in parallel to one of the specifications in Table 8. For these tables, each column is the effects from a single independent variable and each row is the change in the likelihood of an agent receiving that number of stars for a one unit change in the variable. The results are consistent with those from Table 8.

Table A.5: Order Probit of Impacts on Rating given to Agent, Selected vs. Other, Model 1

VARIABLES	(1) DIRECTACC	(2) OverEstPick	(3) UnderEstPick	(4) OverEstOther	(5) UnderEstOther
1 Star	-0.0592*** (0.0156)	0.0274*** (0.00486)	0.0122*** (0.00353)	0.00496* (0.00273)	0.0117*** (0.00334)
2 Star	-0.0728*** (0.0156)	0.0337*** (0.00452)	0.0150*** (0.00461)	0.00610* (0.00350)	0.0144*** (0.00320)
3 Star	-0.0485*** (0.0116)	0.0224*** (0.00463)	0.00999*** (0.00363)	0.00406 (0.00251)	0.00962*** (0.00223)
4 Star	0.0404*** (0.00918)	-0.0187*** (0.00361)	-0.00831*** (0.00284)	-0.00338* (0.00205)	-0.00800*** (0.00227)
5 Star	0.140*** (0.0297)	-0.0649*** (0.00753)	-0.0289*** (0.00835)	-0.0117* (0.00656)	-0.0278*** (0.00569)
Observations	1,044	1,044	1,044	1,044	1,044

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Order Probit of Impacts on Rating given to Agent, Selected vs. Other, Model 2

VARIABLES	(1) DIRECTACC	(2) OverEstPick	(3) UnderEstPick	(4) OverEstOther	(5) UnderEstOther	(6) DISC	(7) DirectAccDISC
1 star	-0.0521*** (0.0126)	0.0275*** (0.00491)	0.0122*** (0.00356)	0.00473* (0.00282)	0.0118*** (0.00339)	0.00946 (0.0235)	-0.0139 (0.0300)
2 Stars	-0.0641*** (0.0178)	0.0339*** (0.00442)	0.0150*** (0.00463)	0.00582 (0.00368)	0.0145*** (0.00323)	0.0116 (0.0280)	-0.0171 (0.0357)
3 Stars	-0.0427*** (0.0131)	0.0225*** (0.00453)	0.00996*** (0.00363)	0.00387 (0.00261)	0.00968*** (0.00224)	0.00775 (0.0189)	-0.0114 (0.0237)
4 Stars	0.0355*** (0.0112)	-0.0187*** (0.00360)	-0.00827*** (0.00288)	-0.00322 (0.00216)	-0.00804*** (0.00228)	-0.00644 (0.0153)	0.00947 (0.0195)
5 Stars	0.123*** (0.0293)	-0.0652*** (0.00754)	-0.0288*** (0.00838)	-0.0112 (0.00684)	-0.0280*** (0.00583)	-0.0224 (0.0551)	0.0330 (0.0698)
Observations	1,044	1,044	1,044	1,044	1,044	1,044	1,044

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Order Probit of Impacts on Rating given to Agent, Selected vs. Other, Model 3

VARIABLES	(1) DIRECTACC	(2) OverEstPick	(3) UnderEstPick	(4) OverEstOther	(5) UnderEstOther	(6) DISC
1 Star	-0.0599*** (0.0137)	0.0311*** (0.00549)	0.0185*** (0.00457)	0.00899*** (0.00310)	0.00754*** (0.00242)	0.0161 (0.0301)
2 Stars	-0.0736*** (0.0177)	0.0382*** (0.00487)	0.0227*** (0.00452)	0.0110*** (0.00359)	0.00926*** (0.00264)	0.0197 (0.0357)
3 Stars	-0.0491*** (0.0126)	0.0255*** (0.00586)	0.0151*** (0.00414)	0.00736*** (0.00259)	0.00618*** (0.00189)	0.0132 (0.0247)
4 Stars	0.0404*** (0.0117)	-0.0210*** (0.00441)	-0.0124*** (0.00335)	-0.00606*** (0.00227)	-0.00508*** (0.00177)	-0.0108 (0.0194)
5 Stars	0.142*** (0.0280)	-0.0739*** (0.00902)	-0.0438*** (0.00868)	-0.0213*** (0.00660)	-0.0179*** (0.00479)	-0.0381 (0.0709)
Observations	1,044	1,044	1,044	1,044	1,044	1,044

VARIABLES	(7) DirectAccDISC	(8) UnderEstPickDisc	(9) OverEstPickDisc	(10) UnderEstOtherDisc	(11) OverEstOtherDisc
1 Star	-0.000301 (0.0248)	-0.0131* (0.00738)	-0.00737 (0.00597)	0.00873* (0.00525)	-0.00595 (0.00541)
2 Stars	-0.000370 (0.0305)	-0.0161** (0.00787)	-0.00906 (0.00727)	0.0107* (0.00599)	-0.00730 (0.00632)
3 Stars	-0.000247 (0.0203)	-0.0107* (0.00570)	-0.00604 (0.00538)	0.00715* (0.00400)	-0.00487 (0.00410)
4 Stars	0.000203 (0.0167)	0.00881* (0.00471)	0.00497 (0.00423)	-0.00588* (0.00341)	0.00401 (0.00345)
5 Stars	0.000716 (0.0589)	0.0311* (0.0159)	0.0175 (0.0143)	-0.0207* (0.0116)	0.0141 (0.0123)
Observations	1,044	1,044	1,044	1,044	1,044

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1