The Role of Bounded Rationality and Imperfect Information in Subgame Perfect Implementation - An Empirical Investigation

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Abstract

In this paper we conduct a laboratory experiment to test the extent to which Moore and Repullo's subgame perfect implementation mechanism induces truth-telling in practice, both in a setting with perfect information and in a setting where buyers and sellers face a small amount of uncertainty regarding the good's value. We find that Moore-Repullo mechanisms fail to implement truth-telling in a substantial number of cases even under perfect information about the valuation of the good. This failure to implement truth-telling is due to beliefs about the irrationality of one's trading partner. Therefore, although the mechanism should — in theory — provide incentives for truth-telling, many buyers in fact believe that they can increase their expected monetary payoff by lying. The deviations from truth-telling become significantly more frequent and more persistent when agents face small amounts of uncertainty regarding the good's value. Our results thus suggest that both beliefs about irrational play and small amounts of uncertainty about valuations may constitute important reasons for the absence of Moore-Repullo mechanisms in practice.

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1 Introduction

Subgame Perfect Implementation has attracted much attention since it was introduced by Moore & Repullo (1988). A main reason for this success is the remarkable property that almost any social choice function can be implemented as the *unique* subgame perfect equilibrium of a suitably designed dynamic mechanism.[1] This was perceived as a substantial improvement over Nash implementation, which suffered from two main limitations: first, it would allow only a certain class of social choice rules to be implemented, those which are "Maskin Monotonic" (Maskin, 1977; Maskin, 1999); roughly speaking, Nash implementation does not permit the implementation of social choice rules that involve distributional concerns between the agents. Second, Nash implementation typically involves multiple equilibria, so that even if a desirable equilibrium exists, an undesirable one may too.[2]

A common objection to subgame perfect implementation mechanisms, however, is that they are hardly observed in practice. This in turn raises the question as to why one does not observe them. A first type of answer, developed by Fudenberg, Kreps & Levine (1988), is that the behavioral assumptions embedded in subgame perfection may not be a good approximation of actual behavior. Another type of answer, recently put forward by Aghion, Fudenberg, Holden, Kunimoto & Tercieux (2012), henceforth AFHKT, is that subgame perfect implementation is not robust to arbitrarily small deviations from common knowledge.

In this paper we use a laboratory experiment to test the extent to which the Moore-Repullo mechanism implements truth-telling in practice, both in a setting with perfect information and in a setting where buyers and sellers do not share common knowledge about the good's valuations. We implement three treatments: one with perfect information about the value of the good (we refer to it as the no-noise treatment); one with 5% imperfect information (i.e., traders receive information about the good's valuation that is 95% correct); and one with 10% imperfect information (traders have information that is 90% correct). We also conducted a robustness check with only 1% imperfect information to examine whether even very small deviations from complete information can cause serious failures in inducing truth-telling.

Our environment is taken from Hart & Moore (2003) where a seller is about to receive a buyer-specific good of either high or low quality. Before learning the value of the good, the buyer and seller would like to write a contract where the buyer pays a high price if the good

[1] Subgame perfect implementation also assumes that individuals are sequentially rational and that transfers of any size are allowed.

[2] Uniqueness can be obtained through the use of so-called "integer games" whereby parties simultaneously announce an integer and the player with the largest announcement has her preferred option implemented. These have been widely criticized, particularly since the infinite strategy means that best responses are not well-defined (Jackson 1992), and for being unimportant in practice.

is of high quality and a low price if the good is of low quality. However, the quality of the good is not verifiable by a third-party court and thus a state-dependent contract cannot be directly enforced.

While the state is not verifiable, public announcements can be recorded and used in legal proceedings. Thus the two parties can in principle write a contract that specifies trade prices as a function of announcements made by the buyer. If the buyer always tells the truth, then his announcement can be used to set state-dependent prices. One way of doing this is to implement a mechanism that allows announcements to be challenged by the seller and to punish the buyer any time he is challenged. If the seller challenges only when the buyer has told a lie, then the threat of punishment will ensure truth-telling.

The key challenge of developing the implementation mechanism is to construct a set of actions such that the seller has an incentive to challenge lies but to prevent the seller from challenging the buyer when he has in fact told the truth. The SPI mechanism we consider accomplishes this by having a sellers challenge trigger two actions: a punishment, in the form of a fine, and a counter-offer. This counter-offer is structured so that if the buyer was lying he will accept the counter-offer and if he was telling the truth he will reject it. By conditioning additional award and punishments to the seller based on whether the counter-offer was accepted or rejected, the mechanism can prevent sellers from abusing their power by challenging when the buyer had indeed told the truth.

For the SPI mechanism to induce truth-telling, it must be structured so that (i) buyers have an incentive to accept counter-offers after a lie and to reject counter-offers after the truth and (ii) sellers have an incentive to challenge lies and not challenge truthful announcements. When experimenting with the SPI mechanism outlined above under full information, we find that the mechanism is very successful in inducing these behaviors. In line with what the theory would predict, buyers always reject counter-offers after a truthful announcement and accept counter-offers over 90% of the time after a lie; sellers challenge lies over 90% of time and challenge truthful announcements in less than 5% of cases.

Surprisingly, however, the mechanism in our full information treatment fails to induce truth-telling in a substantial number of cases. Despite correct pecuniary incentives, buyers who observe a high quality good lie over 30% of the time and about 10% of buyers lie in every period. Based on beliefs data, these lies appear to be due to buyers who are pessimistic about the rationality of the sellers and fear that truthful announcements will be challenged.

To better understand the extent to which beliefs are playing a role, we ran an additional treatment where we elicit incentive compatible beliefs using a mechanism developed by Karni (2009). We find that not only do the majority of individuals who lie believe that they have a higher expected pecuniary payoff for lying than for telling the truth, but the majority of

individuals who tell the truth also hold these beliefs. This finding is due primarily to a large majority of buyers who believe that truth-telling may be challenged. Thus paradoxically, while the mechanism is designed to induce truth-telling based on pecuniary incentives, the mechanism is in fact associated with beliefs that render lying profitable for the buyers — even for the majority of buyers who tell the truth. Thus, it appears that a substantial amount of the observed truth-telling is not due to the mechanism but to the buyers' intrinsic preferences for honesty.

Next, we analyze how the SPI mechanism performs in the presence of imperfect information. More specifically, we introduce two noise treatments where we give buyers and sellers imperfect signals about the underlying quality of the good which are correct either 90% or 95% of the time. According to AFHKT the introduction of noise should induce buyers to believe that lying, i.e., the announcement of a low value after a high signal, is less likely to be challenged by the sellers. For this reason, the buyers are also predicted to increase their rate of lying. We find that these predictions are well supported in the data. The introduction of noise increases the proportion of buyers who announce a low value with a high signal by 15 to 25 percentage points relative to the no-noise treatment. These buyer lies are persistent in the noise treatment and do not diminish with experience. Further, the introduction of noise causes a significant change in buyers' beliefs; they are now much more likely to believe that lying will not be challenged. In addition to the patterns predicted by AFHKT, we observe that the introduction of noise also exacerbates a pattern that we already observed in the perfect information treatment: the buyers have even more pessimistic beliefs about being challenged after truth-telling although — according to the theory — truthful announcements should never be challenged.

In a further experiment, we study how the introduction of even small amounts of noise impacts the mechanism. In a treatment where individuals are given the correct signal 99% of the time, we find that the introduction of noise increases buyer lies to the levels observed in the 95% noise treatment. Thus, even very small deviations from common knowledge can have a big effect on the outcome of the mechanism.

The buyers' beliefs that even truthful announcements will be challenged by the sellers seems to play an important role for the mechanism's failure to induce truth-telling both under complete and incomplete information. But does this belief indeed cause buyers' lies? To examine this question, we also study what Moore (1992) refers to as a simple mechanism where we prevent buyers from being challenged if they announce a high valuation for the good. This simple mechanism can implement the first best in our setting but would not function in more complicated environments where both parties must announce truthfully. In a treatment of this mechanism with no noise, the new mechanism dramatically reduces

the proportion of buyer lies, providing direct evidence that strategic uncertainty is driving most of the lies in the no-noise treatments. With noise, however, buyer lies continue to be common. Overall, our findings suggest that small amounts of private information do indeed lead to large deviations from truth-telling and significantly more lies than under perfect information.

This paper relates to several strands of literature. It first contributes to the literature on mechanism design and more specifically on subgame perfect implementation (Maskin, 1999; Moore & Repullo, 1988; Maskin & Tirole, 1999a; Chung & Ely, 2003) by pointing to two main sources for the failure of SPI mechanisms: namely, players' beliefs about the possibility of irrational challenges by other players, and (small) deviations from common knowledge. In particular we show that beliefs about the irrationality of the trading partner undermine the SPI mechanism even in the case of perfect information about the good's value. This in turn suggests that future work should concentrate on the design and examination of mechanisms that are robust to deviations from perfect information and perfect rationality.[3] Our results also point to a preference for truth-telling that causes some individuals to go against their belief-based pecuniary payoffs and make truthful announcements. This result suggests that it may be possible to design more efficient implementation mechanisms that utilize these preferences for honesty.[4]

Second, our paper contributes to the debate on the foundations of incomplete contracts. In their influential 1986 paper, Grossman and Hart argued that in contracting situations where states of nature are observable but not verifiable, asset ownership (or vertical integration) can help limit ex post hold-up and thereby encourage ex-ante investments (see Grossman & Hart (1986)). However, in subsequent work, Maskin & Tirole (1999a, 1999b) used subgame perfect implementation to show that the non-verifiability of states of nature can be overcome using a 3-stage subgame perfect implementation mechanism which induces truth-telling by all parties as the unique equilibrium outcome. Our paper sheds light on why such mechanisms are not observed in practice, which in turn helps explain why vertical integration or control allocation matter.

Finally, our paper also contributes to the experimental literature on implementation. Sefton & Yavas (1996) study extensive-form Abreu-Matsushima mechanisms that vary in the number of stages used and find that incentive-compatible mechanisms with 8 and 12 stages perform worse than a mechanism with 4 stages that is not incentive compatible.

[3]The systematic under estimation of the rationality of others is similar to results in Huck & Weizsäcker (2002) who find that beliefs about the play of others are distorted towards the uniform prior.

[4]Our result that many individuals tell the truth when their monetary gain from truth-telling is negative is related to the literature on lying aversion (Gneezy, 2005; Sanchez-Pages & Vorsatz, 2007; Ederer & Fehr, 2009).

Katok, Sefton & Yavas (2002) study both simultaneous and sequential versions of the Abreu-Matsushima mechanism and conclude that individuals use only a limited number of iterations of dominance and steps of backward induction. Based on these papers, we limited out attention to mechanisms that require only two levels of backward induction.[5] Fehr, Powell, & Wilkening (2014) study a related subgame-perfect implementation mechanism in the context of a hold-up problem. They find that reciprocity and other-regarding preferences cause the SPI mechanism to fail: The mechanism often does not solve the hold-up problem and the trading parties have generally higher pecuniary returns in the absence of the mechanism such that they refuse to enter the mechanism in the majority of the cases. In the current paper we intentionally designed our mechanism and environment in such a way that reciprocity was unlikely to play a role.[6] Therefore, we could concentrate on how imperfect information and other forces such as irrational beliefs and strategic uncertainty affect the performance of the mechanism. Our results show that these forces strongly impair the functioning of the mechanism.

The remaining part of the paper is organized as follows. Section 2 presents the simple model which guides our experimental design. Section 3 describes the experiment and hypotheses. Section 4 presents the experimental results under perfect and imperfect information. Section 5 concludes by suggesting broader implications from our experiment and avenues for future research.

2 Theoretical Motivation

In this section we present a simple example which will guide our experimental design.

2.1 Common Knowledge

The following example is a slight modification of one used in AFHKT, and based on Hart & Moore (2003).[7] There are two parties, a B(uyer) and a S(eller) of a single unit of an

[5] An extensive experimental literature also exists looking at efficiency of implementation mechanisms in the public goods provision problem. Chen & Plott (1996), Chen & Tang (1998), and Healy (2006) study learning dynamics in public good provision mechanisms. Andreoni & Varian (1999) and Falkinger, Fehr, Gachter, & Winter-Ebmer (2000) study two-stage compensation mechanisms that build on work from Moore-Repullo (1988), while Harstad & Marese (1981, 1982), Attiyeh, Franciosi, & Isaac (2000), Arifovic & Ledyard (2004), and Bracht, Figueres, & Ratto (2008) study the voluntary contribution game, Groves–Ledyard, and Falkinger mechanisms respectively. Masuda, Okano & Saijo (2014) study approval mechanisms and emphasize the need for implementation mechanisms to be robust to multiple reasoning processes and behavioral assumptions.

[6] We deliberately chose parameters in our experiment that made reciprocal behavior very costly and thus very unlikely to occur. We show this more explicitly in Section 3.3.1.

[7] The original example is also reported in Aghion & Holden (2011).

indivisible good. If trade occurs then B's payoff is $V_B = \theta - p$, where θ is the value of the good and p is the price. S's payoff is just $V_S = p$.

The good can be of either high (the state is $\theta = \theta^H$) or low quality ($\theta = \theta^L$). If it is high quality then B values it at 70, and if it is low quality then B values it at 20. Before θ is realized both parties would prefer to trade at a price $p(\theta) = \frac{\theta}{2}$. This price always ensures that trade occurs when it is efficient and splits the surplus evenly between the buyer and the seller in all states of the world so that inequity aversion does not influence the desire for trade.

The value θ is *observable* and common knowledge to both parties but *non-verifiable* by a court. The assumption that the value θ is non-verifiable implies that no contract can be written that is credibly contingent on θ. However, truthful revelation of θ can be achieved through the following Moore-Repullo (MR) mechanism which can indirectly generate the desired price schedule:

1. B announces either "high" or "low". If "high" and S does not "challenge" B's announcement, then B pays S a price equal to 35 and the game then ends.

2. If B announces "low" and S does not "challenge" B's announcement, then B pays a price equal to 10 and the game ends.

3. If S challenges B's announcement then:

   (a) B pays a fine of $F = 25$ to T (a third party).

   (b) B is made a counter-offer for the good at a price of 75 if his announcement was "high" and a price of 25 if his announcement was "low."

   (c) If B accepts the counter-offer then S receives the fine $F = 25$ from T (and also the counter-offer price from B) and the game ends.

   (d) If B rejects the counter-offer then S pays $F = 25$ to T. S also gives the good to T who destroys it and the game ends.

When the true value of the good is common knowledge between B and S this mechanism yields truth-telling as the unique subgame-perfect equilibrium. The logic of this equilibrium is that the initial-prices, counter-offer prices, and fines are constructed so that if B and S are commonly known to be sequentially rational, B only has an incentive to announce "high" if $\theta = \theta^H$ and "low" if $\theta = \theta^L$. For this to be true, the mechanism must satisfy three conditions.

(i) **Counter-Offer Condition.** B must prefer to accept any counter-offer for which he has announced "low" when $\theta = \theta^H$. B must prefer to reject any counter-offer for which he has announced "low" when $\theta = \theta^L$ or for which he announced "high".

(ii) **Appropriate-Challenge Condition.** S must prefer to challenge an announcements of "low" when $\theta = \theta^H$ and must prefer not to challenge an announcement of "low" when $\theta = \theta^L$. S must prefer to never challenge "high".

(iii) **Truth-Telling Condition.** B must prefer to announce "low" if $\theta = \theta^L$ and "high" if $\theta = \theta^H$.

We refer to challenging "low" when $\theta = \theta^H$ as an **appropriate challenge**. The Counter-Offer Condition requires that after an appropriate challenge, the counter-offer price is below the value of the good so that B has a pecuniary incentive to accept the counter-offer. Since the counter-offer price after "low" is 25, this requirement is met. The Counter-Offer Condition also requires that after any other challenge, the counter-offer price is above the value of the good so that B has a pecuniary interest to reject the counter-offer. Since the counter-offer prices for "low" is 25 and the counter-offer price for "high" is 75, this second requirement is met.

As prices and counter-offers are constructed to satisfy the Counter-Offer Condition, B will reject counter-offers following inappropriate challenges and will accept counter-offers following appropriate challenges. This implies the Appropriate-Challenge Condition is satisfied if S has an incentive to challenge only in cases when B will accept such a challenge (i.e., when B announces "low" when $\theta = \theta^H$). This condition is satisfied since the counter-offer price of challenging a "low" announcement (25) plus the fine (25) exceeds the price that occurs if the announcement is not challenged (10).

Finally, for the Truth-Telling Condition to be satisfied, B must prefer to announce "low" if $\theta = \theta^L$ and "high" if $\theta = \theta^H$. Since the price paid by announcing "high" is higher than the price paid by announcing "low" and an appropriate challenge never occurs when $\theta = \theta^L$, B never has an incentive to overreport his value by announcing "high" when $\theta = \theta^L$. Further, B will always be challenged for announcing "low" when $\theta = \theta^H$. Adding the counter-offer price and the fine, a buyer's total payment if he **lies** by announcing "low" when $\theta = \theta^H$ is 50. As the price paid for announcing "high" is 35 and lower than the total payments from lying, B has no incentive to underreport and announces truthfully when $\theta = \theta^H$ as well.

Thus the above mechanism yields unique implementation in subgame perfect equilibrium. That is, for any realization of θ, there is a unique subgame perfect equilibrium which yields different prices for different valuations of the good. Moreover, in each state, the unique subgame perfect equilibrium is appealing from a behavioral point of view since it consists of telling the truth and it splits the surplus equally among B and S. Both of these properties fail once we introduce small common p-belief perturbations.

2.2 The Failure of Truth-Telling Under (Small) Informational Perturbations

We now introduce a small common p-belief perturbation from common knowledge about the valuation θ. We assume (i) the players have a common prior μ, (ii) $\mu(\theta = \theta^H = 70) = .5$, and (iii) $\mu(\theta = \theta^L = 20) = .5$.[8] Each player receives an independent draw from a signal structure with two possible signals: s^H or s^L, where s^H is a high signal where θ equals 70 with probability $1 - \epsilon$, and s^L is a low signal where θ is equal to 20 with probability $1 - \epsilon$. We use the notation s_B^H (resp. s_B^L) to indicate that B received the high signal s^H (resp. the low signal s^L).

First, as in AFHKT, we can show that there is no equilibrium in pure strategies in which the buyer and seller always report truthfully. To see this, suppose instead that such an equilibrium exists, and further suppose that B gets signal s_B^L, announces "low," and is challenged. Under a truth-telling equilibrium, the buyer's belief is that his signal and the seller's signal are incorrect with equal probability, and thus the expected value of the good is 45. As this is above the counter-offer price of 25, the buyer has an incentive to purchase regardless of his signal.

Anticipating the acceptance of challenges with a low signal and "low" announcement, the seller now has an incentive to challenge even if his signal is s_S^L. It follows that there does not exist an equilibrium where all parties are truth-telling in pure strategies. For slight changes in the environment, a similar pattern can hold in the case of a buyer who receives signal s_B^H and is considering whether to make the "high" or "low" announcement. In this case, under the truth-telling equilibrium, the seller will be unsure as to the value of the good and may not challenge the announcement if she believes the buyer will reject the counter-offer.[9]

AFHKT further show that when introducing even a small level of noise, the set of consistent beliefs expands markedly, which gives rise to equilibria that involve a positive amount

[8] AFHTK consider a more general setting with an arbitrary prior. However, to map closest to the experiment, we develop the theoretical part with the same values, priors, and error distributions as those used in the actual experiment in the next section.

[9] These arguments extend to the limiting case where the value perturbations get very small. AFKHT show that one can find a sequence of p-belief value perturbations parameterized by some noise variable ε, such that convergence to common knowledge corresponds to $\varepsilon \longrightarrow 0$, but truth-telling by the buyer (call it the "good" equilibrium) is not approximately implementable as a mixed strategy sequential equilibrium of the above MR mechanism when $\varepsilon \longrightarrow 0$. They also show that one can find a sequence of p-belief value perturbations parameterized by some noise variable ε and converging to common knowledge as $\varepsilon \longrightarrow 0$, such that the above MR mechanism under these perturbations admits a "bad" sequential equilibrium in which the probability of the buyer misreporting her signal remains bounded away from zero as $\varepsilon \longrightarrow 0$. More generally, AFHKT show that, given any mechanism which "subgame-perfect" implements a non-monotonic social choice function $f(\theta)$, there always exists arbitrarily small common p-belief value perturbations under which a "bad" sequential equilibrium, whose outcome remains bounded away from $f(\theta)$ for at least one state of nature θ, also exists.

of lies by buyers and/or false challenges by sellers. We consider particular deviations from perfect information and derive the corresponding mixed strategy Perfect Bayesian Equilibria (PBEs) in the experimental design section.

3 The Experiment

3.1 The Subgame-Perfect Implementation Game

At the center of our experimental design is a computerized version of the Subgame-Perfect Implementation game we discussed in the previous section. In each of twenty periods, a buyer is matched with a seller and randomly assigned one of two sealed containers.[10] One container is worth 70 ECU to the buyer while the other container is worth 20 ECU.[11] Containers are selected with equal probability and both the buyer and seller do not initially know which container has been chosen while trading.

Each of the two containers is filled with red and blue balls whose composition changes by treatment:

1. **No-Noise Treatment:** In the no-noise treatment, the container worth 70 ECU is filled with 20 red balls and 0 blue balls. The container worth 20 ECU is filled with 20 blue balls and 0 red balls.

2. **5% Noise Treatment:** In the 5% noise treatment, the container worth 70 ECU is filled with 19 red balls and 1 blue ball. The container worth 20 ECU is filled with 19 blue balls and 1 red ball.

3. **10% Noise Treatment:** In the 10% noise treatment, the container worth 70 ECU is filled with 18 red balls and 2 blue balls. The container worth 20 ECU is filled with 18 blue balls and 2 red balls.

At the beginning of each period, one of the balls in the container assigned to the buyer is randomly drawn and secretly shown to the seller. This ball is put back into the container and a second ball is randomly drawn for the buyer but held privately to one side. These signals provide perfect information regarding the container being traded in the no-noise treatment

[10] Subjects are randomly assigned the role of a buyer or of a seller and remain in this role throughout the experiment.

[11] The experiment was conducted in experimental currency (ECU) and converted to Australian dollars at a rate of 10 ECU = 1 AUD.

and almost perfect information in the 5% and 10% noise treatments.[12]

Before the buyer knows the color of his ball he is asked to make a public announcement concerning the value of the container for the case in which the ball drawn for him is red or blue. He may announce a value of either 70 ECU or 20 ECU in each of the two cases. After making choices for both possible signals, the color of the ball drawn is revealed to him and his declared strategy is implemented by the computer. This strategy method gives us a complete set of announcement data in each period which precludes changes in the frequency of lies over time due to random assignment of signals to different subsets of buyers. The strategy method also allows for a complete panel of choices which improves our ability to control for heterogeneity across individuals.[13]

The public announcement of the buyer is next seen by the seller as well as a computerized arbitrator who acts as the implementation mechanism. After observing the announcement, the seller has the option of accepting the announcement or calling the arbitrator. If the seller accepts the announcement, trade occurs at a price equal to 1/2 of the announcement. If, however, the seller elects to call the arbitrator, the buyer is immediately charged a fine of 25 ECU and the game continues on to the arbitration response stage.

In the arbitration response stage, the buyer is given a counter-offer by the computerized arbitrator which is based on his initial announcement. If he announced a value of 70 ECU, the arbitrator gives a counter-offer of 75 ECU. If he announced a value of 20 ECU, the arbitrator gives a counter-offer of 25 ECU.

If the buyer accepts the counter-offer, trade occurs at the counter-offer price. In this case the seller is given the 25 ECU which was previously charged as a fine to the buyer. If, however, the buyer rejects the counter-offer, no trade occurs and the seller is also charged a fine of 25 ECU yielding a loss of 25 ECU for both parties. Note that the structure of fines ensures that under full information the subgame-perfect equilibrium is unique.[14]

In the event that trade occurs, the actual value of the container is revealed and the profits of the buyer and seller are realized based on the value of the container, the price, and any fines. The profits of each individual are calculated after each period.

In addition to action profiles of the implementation mechanism, we also elicited beliefs

[12] In the control quiz, subjects are asked to calculate the likelihood of the other party having the same color ball as them in each treatment. For the no-noise treatment we announce in the verbal summary that "if you see a red ball, you know with 100% certainty that your matched partner has also seen a red ball. Likewise, if you see a blue ball, you know with 100% certainty that your matched partner has also seen a blue ball." For the noise treatments we announce the probability that both parties observe the same signal.

[13] We ran two pilot sessions without the strategy method. The lying rates in these pilot sessions were similar to those reported in the results section.

[14] The mechanism can also be made renegotiation proof by allowing for Nash bargaining in the case of disagreement and placing the fines in escrow so they cannot be recovered in cases of disagreement.

about the likelihood of actions of the other party. Likelihoods were recorded using a 4-point likert scale (Never/Unlikely/Likely/Always). The belief elicitation was done in each period directly after the buyer or seller took their action. For a buyer, we elicited the likelihood that the seller would challenge an announcement of 20 ECU and 70 ECU in each period given his observed signal, and we did so right after the buyer made her announcement decision but before discovering the seller's action. For a seller, we asked about his beliefs right after the seller made his challenge decision. We asked each seller the likelihood that their challenge would be rejected given their signal and the announcement of the buyer.

We did not pay subjects for their beliefs because in the main sessions we were primarily interested in the behavioral data. If we had compensated subjects for both their beliefs and their actions, risk averse subject could have found it optimal to hedge risk by stating beliefs which differ from their true estimates - a possibility that is discussed in more detail in Blanco, Engelmann, Koch & Normann (2010). Moreover, we ran four additional sessions to check whether belief elicitation affects behavior. In these sessions subjects faced 5% noise for 10 periods and then no noise for 10 periods. We find no behavioral differences between these control sessions and the main sessions with the same treatment ordering and with belief elicitation. In particular, the distribution of buyer announcements after a high signal neither differs in the 5% noise treatments (Mann-Whitney-Wilcoxen test, p-value = .3930) nor in the no-noise treatments (Mann-Whitney-Wilcoxen test, p-value = .3303).

3.2 Experimental Design and Protocols

Our experimental design utilizes a within-subjects design in which each subject is exposed to 10 periods of the no-noise treatment and 10 periods of one of the two noise treatments. A total of 16 sessions were run: eight with a 5% noise level and eight with a 10% noise level. We conducted half the sessions starting with the no-noise treatment and switching to the noise treatment in period 11. We reversed the order of the two treatments in the remaining sessions. Each session contained between 20 and 24 subjects who were evenly divided between buyers and sellers at the beginning of the experiment. Buyers and sellers were matched with each other at most once in each of the two treatments.

	Treatment 1	**Treatment 2**	**Number of Subjects**
Session 1-4	No Noise	5% Noise	88
Session 5-8	5% Noise	No Noise	84
Session 9-12	No Noise	10% Noise	90
Session 13-16	10% Noise	No Noise	86

Table 1: Treatments and Observations - 10 Periods per Treatment

All of the experiments were run in the Experimental Economics Laboratory at the University of Melbourne in September and October of 2009. The experiments were conducted using the programming language z-Tree (Fischbacher 2007). All of the 348 participants were undergraduate students at the University, who were randomly invited from a pool of more than 3000 volunteers using ORSEE (Greiner 2004). An additional 340 participants were recruited in follow-up sessions conducted in 2010 and 2013.

Upon arrival to the laboratory, participants were divided into buyers and sellers and asked to read the instructions. To be as fair as possible to the mechanism, the instructions described the game in detail, explaining each possible signal, announcement, and arbitration action profiles in order to make the payoff consequences of a challenge and the rejection/acceptance of a challenge transparent. The instructions also included a summary table which showed the payoff consequences of each combination of container value, announcements, challenges, and responses to challenges for both the buyer and the seller. The instructions then ended with a set of practice questions which tested subjects' understanding of the signal valuations and the payoff consequences of accepting or rejecting counter-offers after a lie and after a truthful announcement. Once the answers of all participants were checked, the experimenter read aloud a summary of the instructions. The purpose of the summary was to ensure that the main features of the experiment were common knowledge amongst the participants.

Subjects then participated in the main experiment which was conducted in two parts. Subjects first played 10 periods of their assigned treatment, being matched with a different partner on the other side of the market in each period. At the start of period 11, new instructions were distributed concerning the change in information structure between treatments, which were read aloud. Subjects then played 10 additional periods, again matching with the same partner at most once.

Following a short questionnaire in which gender and other demographic information were recorded, payments to the subjects were made in cash based on the earnings they accumulated throughout the experiment with an exchange rate of 10 ECU to \$1 AUD. In addition, each subject received a show-up fee of \$10. Since payoffs during the experiment could be negative, the subjects could use the show-up fee to prevent bankruptcy during the experiment.[15] The average salient payment at the end of the experiment was \$51.10 AUD. At the time of the 2009 experiments \$1 AUD = \$0.80 USD.

[15]While we had no bankruptcies in the experiment, there is a potential that the description of bankruptcy rules could prime individuals to be more loss averse in the experiment. To check for this, the additional control treatments without beliefs paid only for a single period and increased the show-up fee to \$35 to cover the worst outcome. We find no significant difference in our results.

3.3 Hypotheses

3.3.1 The No-Noise Treatment

The Moore-Repullo mechanism used in our experiment is designed to implement truthful announcements and efficient trade. Our predictions in the no-noise treatment are as follows:

Hypothesis 1 *In the no-noise treatment buyers truthfully announce their signals and sellers do not challenge these announcements.*

As discussed in the theoretical section, Hypothesis 1 is based on three conditions that must be satisfied in order for the mechanism to function: the counter-offer condition, the appropriate-challenge condition and the truth-telling condition. Each of these conditions has implicit assumptions about how individuals behave and require at least some consistency between an individual's beliefs and the actions of other individuals at later stages of the game. We briefly discuss some of the potential issues that might cause the conditions underlying the mechanism to be violated.

The counter-offer condition requires that a buyer who is appropriately challenged is willing to accept the counter-offer instead of rejecting it. If individuals care only about their own payoffs in the mechanism, as is assumed by theory, this condition is satisfied for any counter-offer price that is below the value of the good in the high state and above the value of the good in the low state. Given our two-state design, any counter-offer price between 20 and 70 would thus suffice in creating a pecuniary incentive to accept appropriate challenges.

As discussed in detail in Fehr, Powell & Wilkening (2014), there is strong evidence of non-pecuniary benefits for rejecting an appropriate challenge when individuals are negatively reciprocal. A buyer who lies and is challenged suffers a pecuniary reduction in his income that unambiguously reduces his utility relative to what he would receive if he had not been challenged. If buyers view this reduction in their payment as an unkind act they may retaliate against sellers by rejecting appropriate counter-offers. This implies that for the mechanism to function properly, the monetary gain from accepting the counter-offer must exceed the combined pecuniary and non-pecuniary values of rejecting.

As we wanted to concentrate in this paper on the impact of imperfect information, irrational beliefs and strategic uncertainty on the functioning of SPI mechanisms, we chose experimental parameters that were likely to rule out negative reciprocity. In this context, we were particularly concerned with the counter-offer condition and used parameters that both maximized the net pecuniary value from accepting the counter-offer and minimized the non-pecuniary value for rejecting. To maximize the pecuniary value, we set the counter-offer price at 25 so that the buyer's return for accepting the challenge (45 ECU) is very large. We

also chose a relatively low fine as the desire to retaliate is likely to be influenced by (1) the amount of money lost by being challenged and (2) the amount of the seller's payoffs that can be destroyed by rejecting. On net, a buyer who retaliates after a low announcement must prefer the payoffs of $\{-25, -25\}$ for the Buyer and Seller over payoffs of $\{20, 50\}$. Equivalently, he must be willing to destroy \$.60 of his own money to destroy \$1.00 of the seller's money after a low announcement and a challenge. This is much larger than what is seen in standard ultimatum games. For example, in a \$10 ultimatum game such a high level of required reciprocity implies that an offer of \$3.75 is rejected - an event that almost never occurs in subject pools such as ours. Moreover, structural estimates of reciprocity using data from Fehr, Powell & Wilkening (2014) indicate that subjects are willing to sacrifice only between \$.25 and \$.4 to destroy \$1 of wealth of the seller after a legitimate challenge in a related subgame perfect implementation mechanism. Thus, if subjects in our experiment display a similar amount of reciprocity, the counter-offer condition is met.[16]

Moving up to the next stage of the game, the appropriate-challenge condition requires that sellers make appropriate challenges but not inappropriate challenges. For this condition to hold it must be that individuals have beliefs about the actions of the buyer that lead to the desired challenge decisions.

While subgame perfection assumes that the beliefs of individuals are consistent with the actions other individuals make in later stages of the game, there are reasons to believe that forming consistent beliefs is particularly difficult in the acceptance and rejection stage. When the counter-offer condition and the appropriate-challenge condition are met, a buyer who announces "low" in the high state is deviating in a way that reduces his material payoffs relative to a truthful announcement. For beliefs to be fully consistent with the subgame-perfect Nash equilibrium, the seller must believe that such a buyer will come back to his senses and accept the counter-offer at the next stage. This consequence of the "one-shot deviation" principle is likely to be violated if, for example, B's lies are correlated with B's choices at a later stage as would be the case if (for instance) lies were generated by confusion.[17]

In order to maximize the incentive of sellers to make challenges across a large range of potential beliefs, we chose to pass the fine F to the seller in the case that the counter-offer is accepted. Given a belief $\rho_s^{L|H}$ that a buyer will reject a counter-offer after a low announcement in the high state, a seller's expected value for challenging is $50(1-\rho_s^{L|H})-25\rho_s^{L|H}$. Comparing this to the return of 10 that the seller could guarantee by not challenging, the seller has a

[16] Our empirical results (see Section 4.1 and 4.2 and Fig. 2c and 3c) strongly support this claim.

[17] See Bolton & Dewatripont (2005) for a general discussion of this issue in subgame-perfect implementation.

pecuniary incentive to challenge if:

$$50(1-\rho_s^{L|H}) - 25\rho_s^{L|H} > 10 \tag{1}$$

which is satisfied when $\rho_s^{L|H} < .533$. Under risk neutrality, this implies that the seller has an incentive to challenge even if she believes a buyer who lies will randomly accept or reject counter-offers after a lie.

Finally, for the truth-telling condition to hold, it must be that a buyer, given his beliefs about the actions of the seller, has an incentive to make a truthful announcement rather than a lie. For the truth-telling condition to hold, both the buyer's belief about the likelihood of being challenged after a lie and the likelihood of being challenged after a truthful announcement guide his decision. Given belief $\rho_b^{L|H}$ that the buyer will be challenged after a low announcement in the high state, a buyer who will accept the counter-offer receives a pecuniary utility of lying of $60(1-\rho_b^{L|H}) + 20(\rho_b^{L|H})$. Likewise, given belief $\rho_b^{H|H}$ that a truthful announcement will be challenged in the high state, the pecuniary utility of a truthful announcement is $35(1-\rho_b^{H|H}) - 25(\rho_b^{H|H})$. For the buyer to have a pecuniary incentive for truthful announcement in the high state, it must be the case that:

$$35(1-\rho_b^{H|H}) - 25(\rho_b^{H|H}) > 60(1-\rho_b^{L|H}) + 20(\rho_b^{L|H}) \tag{2}$$

or

$$\frac{2}{3}\rho_b^{L|H} > \frac{5}{12} + \rho_b^{H|H}. \tag{3}$$

Note that if $\rho_b^{H|H} = 0$, this requirement would be satisfied for $\rho_b^{L|H} > \frac{5}{8}$.

Informed by the discussion above, we parameterized the model with an eye toward making each of the intermediate conditions as slack as possible. In places where parameters affected multiple constraints simultaneously (such as the fine size or counter-offer price), we erred toward ensuring that the counter-offer condition was satisfied as this condition feeds into the other two conditions. We also set the price in the absence of a challenge equal to half of the buyer's announcement in order to minimize the importance of fairness considerations and make the subgame perfect equilibrium salient.

3.3.2 The Noise Treatments

As soon as one introduces noise in agents' information about the state of nature (i.e about the valuation of the good to be traded), the truth-telling equilibrium vanishes and pure and mixed strategy equilibria arise in which either: (i) the buyer makes announcements which are different to his signal; and/or (ii) the seller challenges announcements which are the same

as her signal. This section discusses these equilibria and shows that the introduction of noise is likely to lead to:

(i) an increase in buyers lies,

(ii) a decrease in the probability that sellers challenge a lie by the buyer,

(iii) an increase in the probability of false challenges, i.e., that sellers challenge low announcement although they received a low signal themselves, and

(iv) a decrease in the probability that buyers reject a false challenge

We begin by discussing a pure strategy sequential equilibrium that exists in the model. For any amount of noise, one can sustain the following "bad" (sequential) equilibrium with the appropriate sequence of beliefs: B announces low (i.e a value of 20 ECU) in stage 1 regardless of his signal, S never challenges in stage 2, and (off-equilibrium) B always rejects a counter-offer made in stage 3 if that stage were to be reached. Note that if some subjects play this equilibrium we should observe an increase in buyers lies because they announce a low value after a high signal. We should also observe a decrease in the probability that sellers challenge these lies.

More specifically, this equilibrium can be sustained as a sequential equilibrium with the buyer's (off-equilibrium) belief that the true state is low ($\theta = \theta^L$) when he is challenged and the arbitrator's counter-offer is made. To establish sequential rationality, we proceed by backward induction. It stage 3, regardless of his signal, B believes with probability one that the state is θ^L. Accepting S's offer at a price of 25 (resp. 75) leads to a payoff of $20-25-25=-30$ (resp. $20-25-75=-80$) whereas rejecting it leads to a payoff of -25. Thus, it is optimal for B to reject the offer. Moving back to stage 2, if S chooses "Challenge," S anticipates that her offer will be rejected by B in stage 3, and thus anticipates that, as ε goes to zero, the payoff is approximately equal to -25 if her signal is high and to -25 if the signal is low. On the contrary, if S chooses "No Challenge," S guarantees a payoff of 10. Thus, regardless of her signal, it is optimal for S not to challenge. Moving back to stage 1, suppose first that B receives the high signal s_B^H. Then, as ε becomes small, B believes with high probability that the true state is θ^H so that his expected payoff from announcing "low" is close to $70-10=60$, greater than 35, which B obtains when announcing "high." Thus, it is optimal for B to announce "low." A similar reasoning applies if B receives the low signal s_B^L. Finally, consistency of beliefs follows by identical arguments to those in AFHKT (footnote 13). Thus, the above is indeed a sequential equilibrium.

A second pure strategy (sequential) equilibrium can be sustained where the buyer always announces high regardless of his signal. In this equilibrium, the buyer's (off-equilibrium)

belief is that the true state is high with probability .1 in stage 2 when he receives the low signal, announces a low valuation, and is challenged. The expected value for accepting the challenge is $.9 \times -5 + .1 \times 45 = 0$. Thus, he is indifferent between accepting and rejecting the challenge. If in stage 1 the buyer believes that the seller will always challenge, the expected value of this sequence of play is -25. The buyer can do strictly better by announcing a high value with the low signal and thereby guarantee himself a return of $.9 \times -15 + .1 \times 35 = -10$. Note that if buyers play this equilibrium we should see an increase in the proportion of buyers making high announcements with the low signal. Buyers taking this action should believe that they will be challenged if they make a low announcement.

In addition to the "bad" pure strategy equilibria described above, the noise treatments also generate a mixed strategy equilibrium which is described in more detail in the appendix to this paper. In this equilibrium, the buyer announces his signal truthfully and the seller who has a low signal and observes a low announcement mixes between challenging and not challenging, which implies that we observe false challenges (i.e., challenging a low announcement after observing a low signal) by the sellers. A buyer in this equilibrium who has followed his signal and announced low in stage 1, and then has been challenged in stage 2, mixes in stage 3 between accepting the challenge and rejecting it. Thus, if some subjects play this equilibrium we should observe that the introduction of noise decreases the probability of rejecting a false challenge.

While different equilibria lead to slightly different point predictions regarding the impact of noise, a property of these equilibria is that total lies by buyers and false challenges by sellers increases when noise is introduced. In addition, the challenges of buyers' lies and the rejection of false challenges decreases. We summarize these prediction in the following hypotheses.

Hypothesis 2 *The likelihood that a buyer announces a low valuation with a high signal is higher in the treatments with imperfect information. The likelihood that a seller challenges a low announcement with a high signal is lower in the treatments with imperfect information.*

Hypothesis 3 *The likelihood that a seller with a low signal challenges a low announcement is higher in the treatments with imperfect information. The likelihood that a buyer accepts such a challenge although he received a low signal is also higher in the imperfect information treatments.*

4 Experimental Results

We describe the results of the experiment in this section. Section 4.1 uses the data from the no-noise treatments to study Hypothesis 1. Section 4.2 uses data on beliefs and from a number of additional experiments to interpret some of the results from Section 4.1. Section 4.3 uses data from both the no-noise and noise treatments to study Hypotheses 2 and 3.

We call a draw of a red ball the **high signal**, a draw of a blue ball the **low signal**, an announcement of 70 a **high announcement** and an announcement of 20 a **low announcement**. As before, we define a **lie** as an announcement by B of a low value after observing a high signal. We define an **appropriate challenge** as a challenge by S of a low announcement with the high signal, an **inappropriate challenge** as a challenge by S of a high announcement with the high signal, and a **false challenge** as a challenge by S of a low announcement with the low signal.

4.1 The Mechanism Under Perfect Information

Under Hypothesis 1, our experimental design predicts that in the no-noise treatment, the counter-offer condition, appropriate-challenge condition, and truth-telling condition will hold. These conditions imply that B will always tell the truth, S will make only appropriate challenges, and B will accept counter-offers if and only if they result from an appropriate challenge. The data from the no-noise treatment provides support for only two of these conditions.

Result 1 *The mechanism fails to induce truth-telling in a substantial number of cases. This occurs despite the fact that sellers appropriately challenge buyers' lies most of the time and buyers accept these (appropriate) challenges and reject false challenges most of the time.*

An interesting feature of Result 1 is that although the trading parties play according to the theoretical predictions after a lie in the vast majority of the cases, the buyers nevertheless lie in a substantial number of cases. Thus, contrary to the predictions of the theory, the buyers are not deterred by the subgame perfect behavior of the trading parties after a lie.

Figure 1 displays the patterns of play we observed in the no-noise treatment of the experiment. The left column examines play when an individual receives a low signal while the right side examines play when an individual receives a high signal. Panel (a) summarizes B's announcement decision, Panel (b) summarizes S's challenge decision, and Panel (c) summarizes B's decision to accept or reject counter-offers. The error bars show 95% confidence intervals of each proportion with standard errors clustered at the individual level.

Panel (a) shows that after a low signal, 97.2% of individuals announce that the value is low. By contrast, after a high signal, 30.8% deviate from the theoretical prediction of Hypothesis 1 and lie. We discuss this deviation from truth-telling in greater detail below after detailing play in the other stages of the game.

Panel (b) shows the proportion of announcements that are challenged after each combination of announcement and signal. As can be seen, a low announcement with a low signal is challenged only 4.1% of the time while a high announcement with a high signal is challenged only 4.8% of the time. This implies that inappropriate challenges rarely occur in the data. By contrast, S's challenge a low announcement with a high signal 93.4% of the time implying that S's almost always make appropriate challenges.

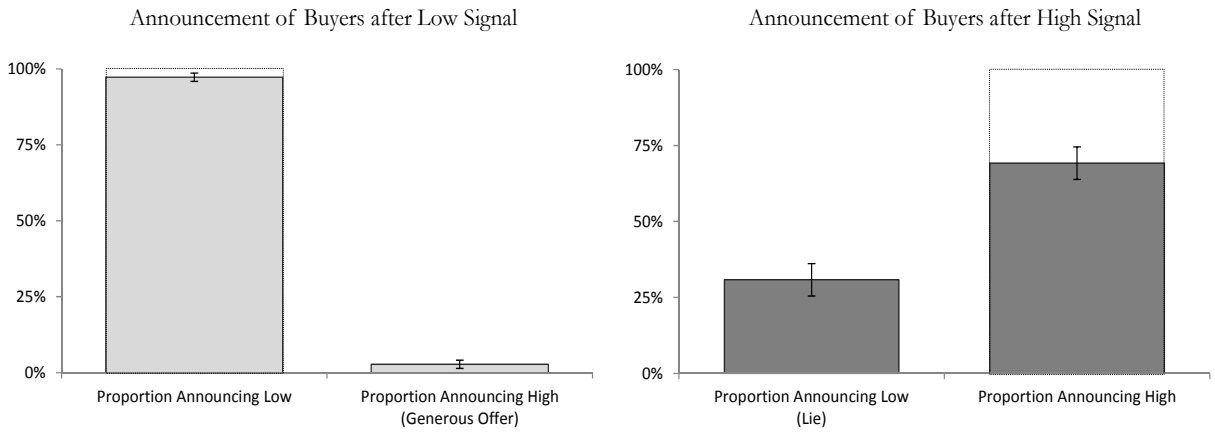
Finally, Panel (c) shows the proportion of counter-offers that are accepted for each combination of announcement and signal. In the case of a high signal, B's always reject counter-offers after truthful announcements and almost always accept counter-iffers after a lie. In the case of a low signal, B's always reject challenges after a low announcement.

While there are small deviations from the theoretical predictions of the model in the challenge stage and counter-offer stage, these deviations tend to vanish over time. Panel (a) of Figure 2 tracks the proportion of truthful announcements that are challenged in each period. This data is overlayed with the predictions and 95% confidence intervals from a simple linear random effects regression that regresses the challenge decision on the period. As can be seen, challenges of truthful announcements are diminishing and the proportion of truthful announcements that are challenged is not significantly different from the theoretical prediction of 0% by period 10. Similarly, as seen on the right side of Panel (b), challenges of lies are increasing over time and the proportion of lies is not significantly different to the theoretical prediction of 100% by period 10. Taken together, the data strongly supports the appropriate-challenge condition.

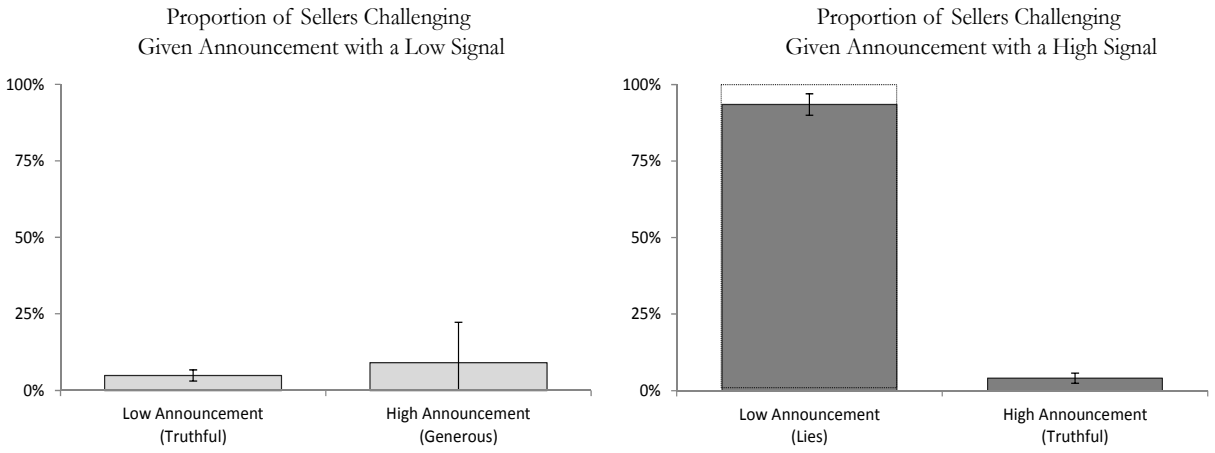
Panel (c) of Figure 2 tracks the proportion of counter-offers that are accepted after a lie over time using the same construction of the prediction line and 95% confidence intervals as in the previous panels. While some B's initially reject counter-offers, the proportion of counter-offers being accepted increases over time and is not significantly different to the theoretical prediction by period 10. Thus, there is strong evidence that the counter-offer condition is met in the data.

Given that the appropriate-challenge condition and the counter-offer condition hold, B's have pecuniary incentives to announce truthfully by construction of the mechanism. Thus, we might expect that lies converge to zero over time. Figure 3 shows that this is not the case. As can be seen in Panel (a), the proportion of B's who are lying is indeed slightly decreasing over time. However, this proportion is above 20% and significantly different from

(a) Announcements of Buyers



(b) Challenges of Sellers



(c) Acceptances of Counter-Offers by Buyers

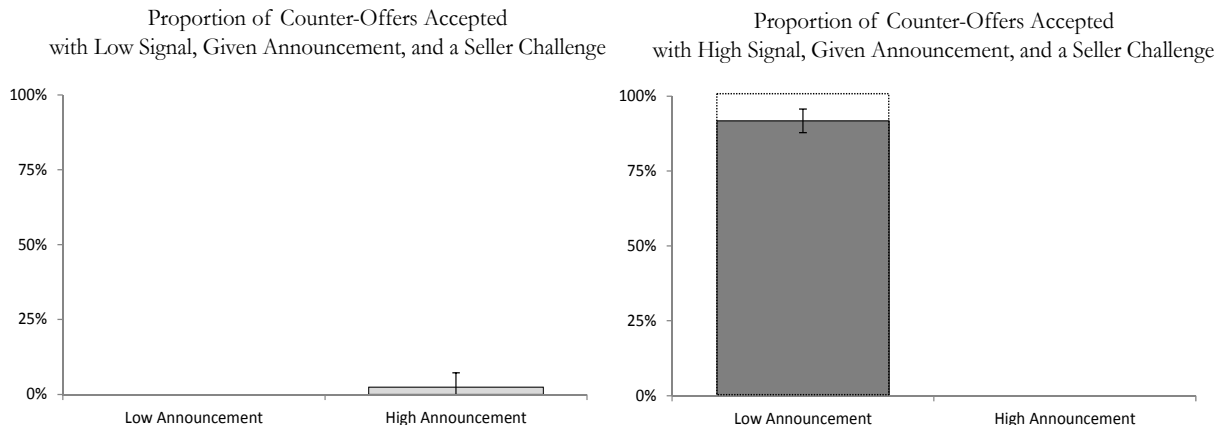
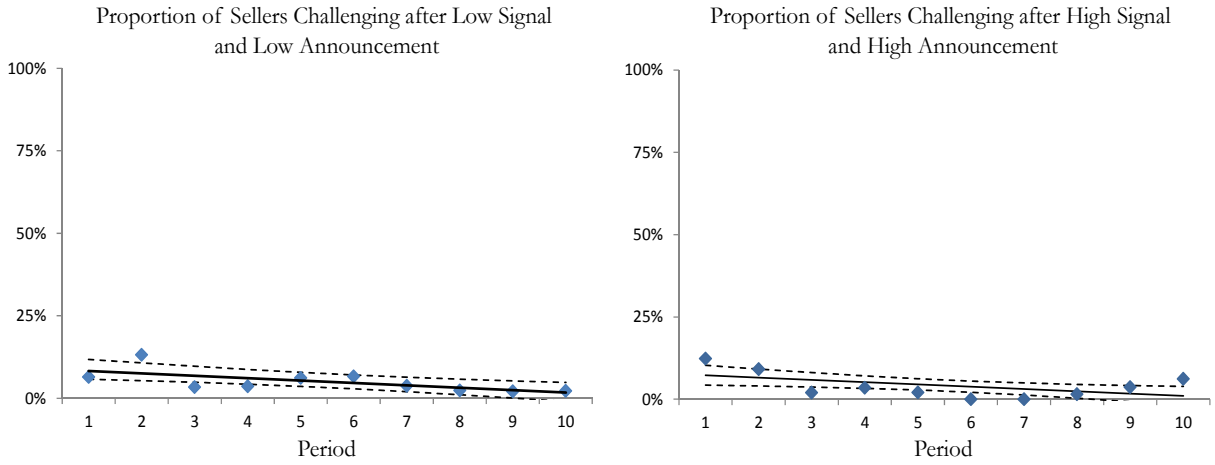
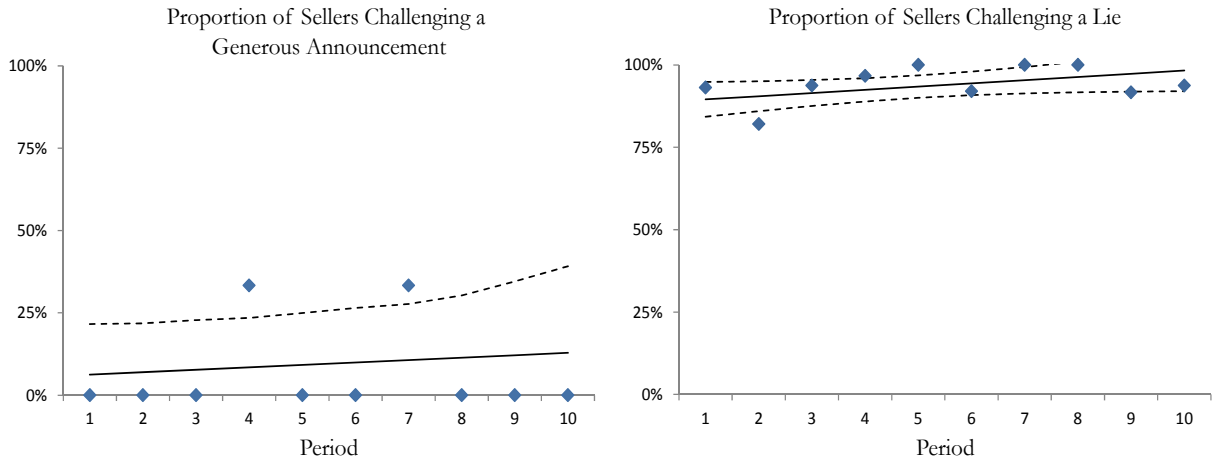


Figure 1: Pattern of Play in No-Noise Treatment

(a) Challenges of Truthful Announcements by Seller over Time



(b) Challenges of Generous Offers and Lies by Sellers over Time



(c) Acceptances of Counter-Offers by Buyers over Time

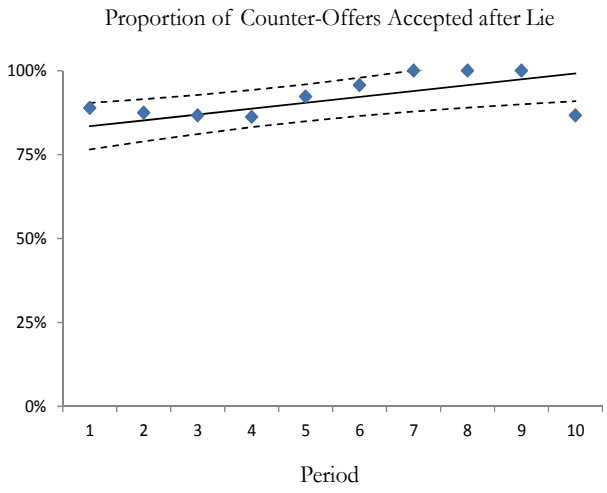


Figure 2: Evolution of Play in Challenge Stage and Counter-Offer Stage of No-Noise Treatment

the theoretical prediction of 0% even in period 10. In fact, looking at the last four periods the rate of lying is constant at roughly 25%.

Panel (b) shows a histogram of B's lie rates in the no-noise treatment using all periods. As can be seen, 38% of B's never lie in the no-noise treatment while 11% of individuals lie in every period. This bimodal distribution becomes more pronounced over time: in a restricted sample of the last five periods of the treatment, 61% of B's never lie while 17% lie in each period. Thus, while many individuals stop lying over time a significant subset of individuals do not stop lying. We explore why these individuals may find it in their interest to lie in the next section.

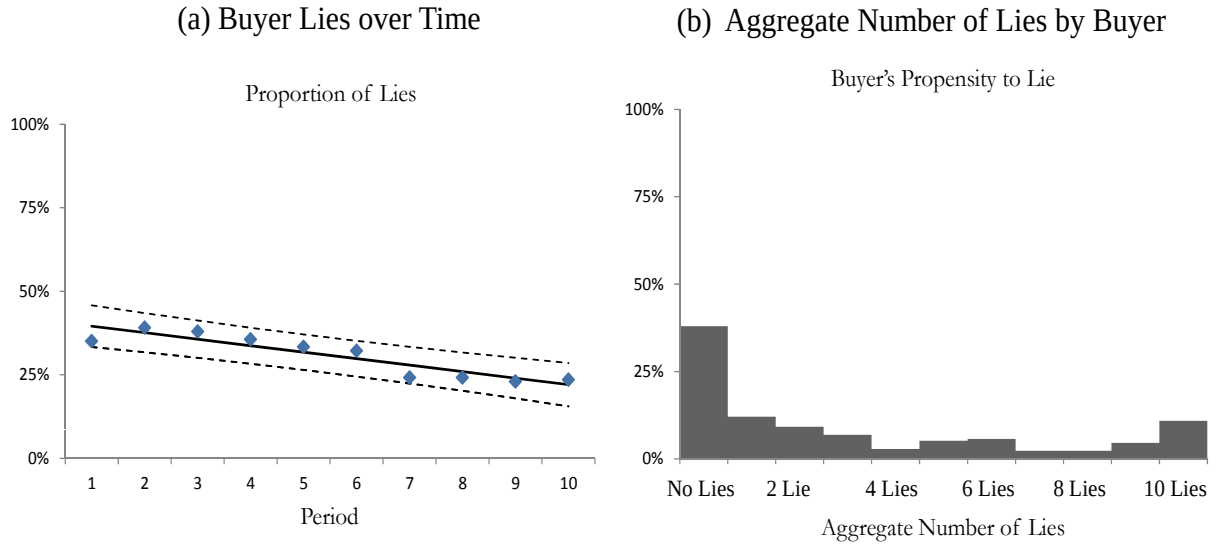


Figure 3: Evolution and Distribution of Lies in Announcement Stage of No-Noise Treatment

4.2 Understanding Deviations from Truth-Telling in the No-Noise Treatment

One potential reason for the failure of subgame-perfect implementation is that individuals must place a large amount of faith in the rationality of other players. B's who announce truthfully must have faith that S's will not make an inappropriate challenge. However, if a B's fear of such an inappropriate challenge is high enough, it may be in his best interest to adopt a strategy that minimizes his potential losses.

In practice, it is relatively rare for S's to make an inappropriate challenge. As was seen in the last section, high announcements were challenged in only 4.8% of observations. Nonetheless, the belief that some S's challenge a truthful high announcement may induce B's to lie. The implemented mechanism implies that a challenged high announcement will

lead to relatively large losses for B regardless of whether B accepts or rejects the challenge. If B accepts the challenge, he will earn 70 - 75 - 25 = -30; if he rejects the challenge, he will earn -25. These losses contrast sharply with the payoff of 20 that B can guarantee himself by lying, being challenged by S, and accepting the counter-offer.

Looking at the beliefs data of B, it appears that the fear of inappropriate challenges is indeed an important determinant of lies. Table 2 reports the results of regression analysis where the dependent variable is 1 if B lies after the high signal and 0 if B makes a truthful announcement. This variable is regressed on the belief that a lie will be challenged and the belief that a truthful announcement will be challenged. To allow for potential non-linearities in the beliefs data we treat B's beliefs as categorical data and split the 4-point Likert scale into a series of dummy variables. We use the category "Never" as the omitted dummy category. Column (1) reports the results of a simple linear probability model with errors clustered at the individual level. Column (2) reports the results of a fixed effects regression with both time and individual level fixed effects.

As can be seen in column (1), B's belief about the likelihood that he will be challenged after a truthful announcement is a good predictor of his likelihood of making a lie. B's are 39.7 (59) percentage points more likely to lie if they believe that a truthful announcement is "Likely" ("Always") to be challenged relative to an individual who believes a truthful announcement will "Never" be challenged. The probability of making a lie is increasing as an individual's beliefs becomes more pessimistic suggesting a monotonic relationship between beliefs and lies. This conclusion also holds if we control for individual and time fixes effects (see column 2)

4.2.1 Precise quantification of beliefs to better understand buyer lies

To explore further the way in which beliefs may be guiding lies in the no-noise treatment we ran an additional experiment in which we elicited probabilistic beliefs of being challenged using an incentive-compatible elicitation mechanism developed in Karni (2009).[18] In this follow-up treatment, we restricted attention to only the no-noise treatment and ran additional periods to study convergence. We ran two sessions with 30 periods and two sessions with 40

[18] Akin to a standard BDM mechanism (Becker, DeGroot & Marschak, 1964), the belief elicitation mechanism gives B a dominant strategy to announce his true beliefs by using B's reported belief to assign him to one of two lotteries — one that is contingent on S's challenge decision and one that is independent of this decision — across a set of binary lottery pairs. We randomly select one of these lottery pairs to be played so that beliefs impact the assignment of B to a lottery but not the explicit characteristics of this lottery. We use the strategy method in this follow up experiment for S's challenge decisions as we want to elicit incentive-compatible beliefs from B about the likelihood of being challenged after a truthful announcement and after a lie. To do so we need to know S's challenge decision for both announcements. See the appendix for full details.

Table 2: Probit Regression of Lies by Buyers

Buyers Belief that Seller will Challenge a High Announcement with High Signal	**(1)**	**(2)**
"Unlikely"	0.065	0.025
	(0.051)	(0.044)
"Likely"	0.397 ***	0.186 ***
	(0.070)	(0.055)
"Always"	0.590 ***	0.234 ***
	(0.074)	(0.063)
Buyers Belief that Seller Will Challenge a Low Announcement with High Signal		
"Unlikely"	-0.027	-0.170 ***
	(0.089)	(0.064)
"Likely"	-0.040	-0.024
	(0.071)	(0.064)
"Always"	-0.127 *	-0.113 *
	(0.066)	(0.059)
Constant	0.249 ***	0.325 ***
	(0.060)	(0.049)
Individual Fixed Effects	No	Yes
Time Fixed Effects	No	Yes
R^2	0.203	0.156
Observations	851	851

Dependent varaible is 1 if the buyer lies by announcing low with a high signal and 0 otherwise. The omitted category is Seller "Never" Challenges. Regression (1) is a linear probability model with errors clustered by individual. Regression (2) is a fixed effect regression with both time and individual fixed effects. *,**,*** denote siginificance at the 10%, 5% and 1% respectively.

periods with random matching across periods. A total of 90 individuals participated in the experiment. The details of this elicitation mechanism can be found in the appendix.[19]

Result 2 *The majority of B's have pessimistic beliefs about being challenged after a truthful announcement of 70. The majority of B's have optimistic beliefs about being challenged after a lie of 20.*

Figure 4 compares the empirical challenge probability of S's to B's belief of being challenged. Both the means and 95 percent confidence intervals shown are calculated from individual averages. As can be seen on the right hand side of the figure, buyers are strongly pessimistic about the likelihood of being challenged after a truthful high announcement. While the empirical probability of being challenged is 9.1%, the average belief is 30.4%. This pessimism is prevalent across the population, with 80.1% of individuals having pessimistic beliefs about being challenged relative to the empirical distribution. The difference of beliefs and the empirical distribution is significant in both a simple t-test ($t = -5.379$, p-value $< .01$) and a Mann-Whitney-Wilcoxen test ($z = -5.125$, p-value $< .01$).[20]

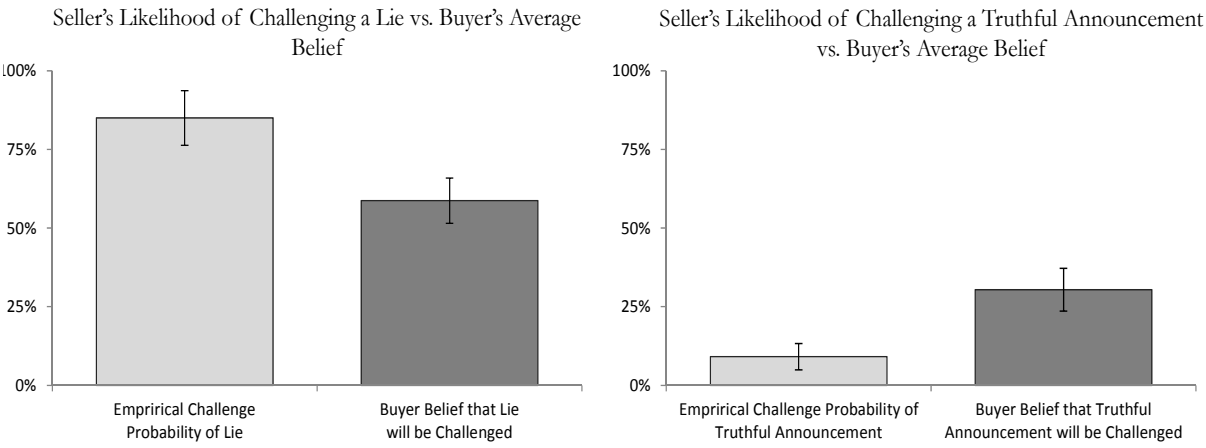


Figure 4: Buyer Beliefs About the Probability of Challenge Relative to Empirical Challenge Probabilities of Sellers

Vice versa, buyers are optimistic about the likelihood of being challenged after a lie with a high signal. While S's challenge 85.0% of the time after a lie (a 15.0% deviation from the Nash

[19] As we were concerned with potential hedging, the follow-up experiment paid only for one period of the experiment and only for the announcement game or the belief elicitation game. There was a 50% chance that the announcement game would be paid and a 50% chance that one announcement-signal combination of the belief elicitation game would be paid.

[20] Observations are an individual buyer's average belief and an individual S's average challenge rate over all periods.

Equilibrium), the average belief is 58.7% (a 41.3% deviation from the Nash Equilibrium). This optimism is again prevalent across the population, with 76.7% of individuals having optimistic beliefs about being challenged relative to the empirical distribution. The difference between beliefs and the empirical distribution is again significant (t-test: $t = 4.703$, p-value $< .01$; Mann-Whitney-Wilcoxen test: $z = 5.56$, p-value $< .01$).

Given the optimistic beliefs about outcomes after a lie and pessimistic beliefs about outcomes after truthful announcing, a natural hypothesis is that B's may believe that they are monetarily better off lying than telling the truth. To test this hypothesis, we use B's reported beliefs to compute the expected value of lying and telling the truth after a high signal if B's respond optimally to a subsequent challenge. We next take the difference between these expected values to estimate the expected monetary gain from truth-telling.

Result 3 *The majority of B's believe they have a higher expected value from lying compared to truth-telling after a high signal. B's with more optimistic beliefs about being challenged after a lie and more pessimistic beliefs about being challenged after a truthful announcement are more likely to lie.*

Figure 5 show the empirical cumulative density functions of the expected gain from truth-telling split between observations where an individuals is lying (N = 543) and observations where an individual is telling the truth (N = 491).[21] As can be seen, the empirical CDF of the expected monetary gain from truth-telling for individuals who tell the truth first order stochastically dominates the CDF for individuals who lie, suggesting that heterogeneity in beliefs is an important factor in the decision to announce truthfully.[22] For both distributions, however, the proportion of individuals where the expected monetary gain from truth-telling is negative is large, with 79.2% (72.7%) of observations where the buyer lies (tells the truth) falling into this category.

One potential reason for the high level of pessimism seen in B's beliefs about being inappropriately challenged is that at least a subset of individuals are choosing announcement strategies that limit their ability to learn over time. 28.9% of individuals lie in each of the last 10 periods of the session and in at least 90% of periods overall. These individuals account for 60.7% of overall lies and 71.7% of lies that occur in the last 10 periods. As a B who

[21] We restrict attention to observations where (i) the buyer believed that announcing low with a high signal had a higher chance of being challenged than announcing high with a low signal and (ii) the buyer announced low with a low signal. There is a very small fraction of individuals in our sample that do not satisfy these plausibility conditions. If we include them, all the qualitative results remain the same and significant.

[22] These distributions are significantly different in a bootstrapped version of the Mann-Whitney-Wilcoxen test where we randomly sampled a single period from each buyer in each iteration. p-value $< .01$. See Datta & Satten (2005) for a discussion.

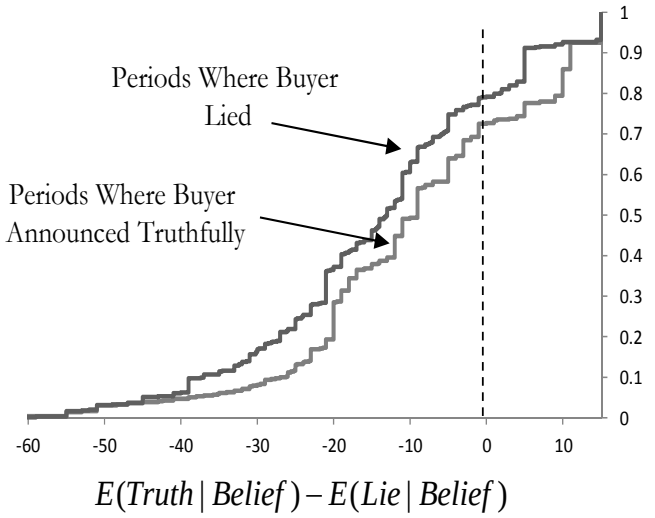


Figure 5: Cumulative Density Function of Expected Gain from Telling the Truth Relative to Lying Split between Observations where the Buyer is Lying (Dark Grey) and Telling the Truth (Light Grey).

lies in each period gets no new information about the likelihood of being challenged after a truthful announcement, the data suggests that alternative self-confirming equilibria may be being selected in the game instead of the predicted subgame perfect equilibrium as a result of B's actions and initial beliefs.[23]

Overall, our data suggests something of a paradox in the functioning of the Moore-Repullo mechanism. While the mechanism was designed to induce truth-telling using pecuniary incentives, most individuals who are truthful are distrustful of their partner and believe that such actions will lead to monetary loss. Truthful announcements are therefore being supported not by pecuniary incentives, but instead by non-pecuniary ones.

4.3 The Mechanism Under Almost-Perfect Information

In the no-noise treatment we observed a non-negligible lack of truth-telling although the mechanism functioned well at the later stages and rarely ended with the buyer rejecting the counter-offer. Our theoretical model predicts that as we introduce imperfect information about the value of the good, additional breakdowns in the mechanism will occur. As described in Hypothesis 2, B's with high signals are predicted to lie with greater frequency

[23]See Fudenberg, Kreps & Levine (1988), Fudenberg and Levine (1993) and Kalai and Lehrer (1993) for a discussion of self-confirming equilibrium. Notice that in our context, the consistent self-confirming equilibrium where B's always lie is a Nash Equilibrium, just not the subgame-perfect equilibrium that we are trying to implement.

and S's are predicted to reject the buyers' lies with lower frequency. Further, as described in Hypothesis 3, S's are predicted to challenge low announcements although they received low signals (what we call a false challenge) and B's are predicted to accept some of these false challenges. We find support for most of these theoretical predictions:

Result 4 *The introduction of noise leads to a significant increase in B's lies and a small but insignificant decrease in challenges of low announcements by S's with a high signal. In addition, the introduction of noise also increases B's belief that even truthful announcements of a high signal will be challenged. Finally, noise also leads to an increase in both false challenges by S's and B's acceptance of challenges with a low signal after a low announcement.*

An interesting aspect of Result 4 is that it confirms theoretically predicted behavioral tendencies that undermine the mechanism but, in addition, the evidence also shows that noise tends to exacerbate problems with the mechanism that we have already observed in the no-noise treatment: B's have more pessimistic beliefs that truthful announcements of a high signal will be challenged in the noise treatment compared to the no-noise treatments. This finding is in contrast to the theoretical prediction that truthful announcements of high signals should never be challenged in any of these treatments.

The left hand side of Figure 6 shows the proportion of B's with a high signal who lie across the three treatments. The error bars show 95% confidence intervals of each proportion with standard errors clustered at the individual level. As can be seen, B's lie in 45.9% of cases in the 5% noise treatment and in 52.2% of cases in the 10% noise treatment. Both of these lie rates are significantly higher than those in the no-noise treatment, where lies occur in 30.8% of cases (p-value $< .01$ in both treatment comparisons). The right hand side of Figure 6 shows that there is a small but insignificant decrease in the challenges of low announcements with the high signal relative to the no-noise treatment, where 93.4% of cases were challenged; in the 5% and 10% noise treatments the proportion of cases challenged were 85.2% and 88.6% respectively (5% noise treatment: p-value = .147; 10% noise treatments: p-value = .351). All three challenge rates are high, however, indicating that it would not be in B's interest to lie if their beliefs were consistent with the empirical challenge distributions of the sellers.

Our theoretical model predicts that the increase in lies in the noise treatment is driven by B's belief that S is less likely to challenge a lie. The left panel of Figure 7, which reports B's belief that a lie will be challenged given a high signal, supports the existence of this channel. In the no-noise treatment 46.1% of individuals believe that a lie will always be challenged, while in the noise treatment only 26.4% of individuals hold this belief. Thus,

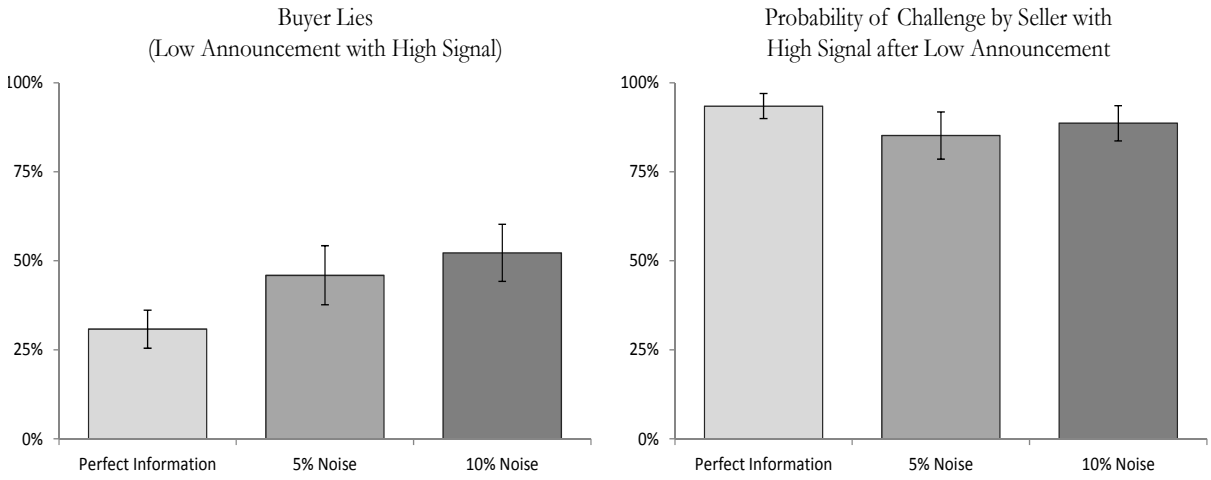


Figure 6: Buyer Lies and Seller's Probability of Challenging with High Signal after a Low Announcement

in the noise treatment the buyers are much more optimistic that they can get away with a lie. This difference in beliefs across the noise treatments and the no-noise treatment is significant based on an ordered probit regression that regresses B's beliefs on the noise treatment dummy ($z = -2.45$, p-value $= .014$, standard errors clustered by individual).

The right panel of Figure 7 shows that the belief pattern observed in the no-noise treatment, namely that B's believe that even truthful announcements of a high value will be challenged, is exacerbated by the existence of noise. While 48.2% of individuals believe that a truthful announcement will never be challenged in the no-noise treatment only 34.9% of subjects in the noise treatments have this belief – a difference that is significant in an ordered probit regression of buyers' beliefs on the noise treatment dummy ($z = -2.21$, p-value $= .027$, standard errors clustered by individual).

Taken together, the belief pattern observed in Figure 7 suggests that there are two reasons why noise increases buyers' lying behavior. First, noise induces B's to believe that a lie is less likely to be challenged and, second, it strengthens the belief that truthful announcements will be challenged. Both reasons reduce the perceived pecuniary benefits from telling the truth relative to telling a lie. We study the causal impact of the second channel on buyers' announcement behavior in both the noise and the no-noise treatment in the next section.

Our results for the noise treatments also support the predictions of Hypothesis 3. Figure 8 shows the proportion of S's who make a false challenge and the proportion of B's who accept a counter-offer after they received a low signal and announced a low value in each of the three treatments. The error bars show 95% confidence intervals of each proportion with standard errors clustered at the individual level. As can be seen on the left hand side, while there are very few false challenges in the no-noise treatment, the proportion of false challenges

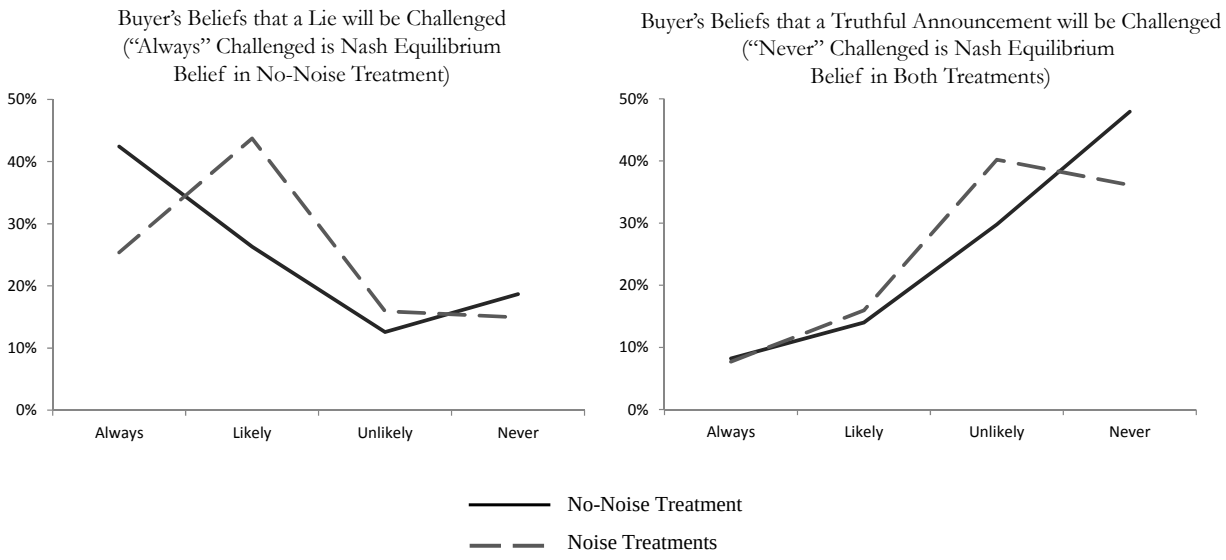


Figure 7: Buyer's Beliefs after High Signal

increases to 20.7% in the 5% noise treatment and 18.8% in the 10% noise treatment. Both noise treatments have significantly more false challenges than in their respective no-noise treatments based on a linear regression with errors clustered at the individual level (p-value $< .01$ in both cases).

As can be seen on the right hand side, B's are also much more likely to accept a counter-offer with a low signal and a low announcement in the noise treatments than in the no-noise treatment. While B's accepted a challenge after a low announcement and a low signal in only 2.4% of observations in the no-noise treatment, they accepted 27.7% of such challenges in the 5% noise treatment and 30.2% of such challenges in the 10% noise treatment. Both noise treatments have significantly more acceptances of counter-offers after a low announcement and a low signal than their respective no-noise treatment based on a linear regression with errors clustered at the individual level (p-value $< .01$ in both cases).

As foreshadowed by the increase in lies and the increase in false challenges that were subsequently rejected, the introduction of noise leads to a marked decrease in earnings. However, this decrease in earnings is asymmetric. As shown in Table 3, B's in the two noise treatments have significant reductions in their earnings relative to that of the no-noise treatment. S's, by contrast, have a very small decrease in earnings. This difference in the outcomes of B's and S's is due to the fact that B's who lie are frequently challenged and accept the counter-offer in over 90% of these cases.

Table 3 also provides an indication about how much surplus is destroyed by the imperfect functioning of the mechanism. As the good is either worth 20 or 70 with equal probability, the expected surplus is 45 if the mechanism induces truth-telling and truth-telling is not

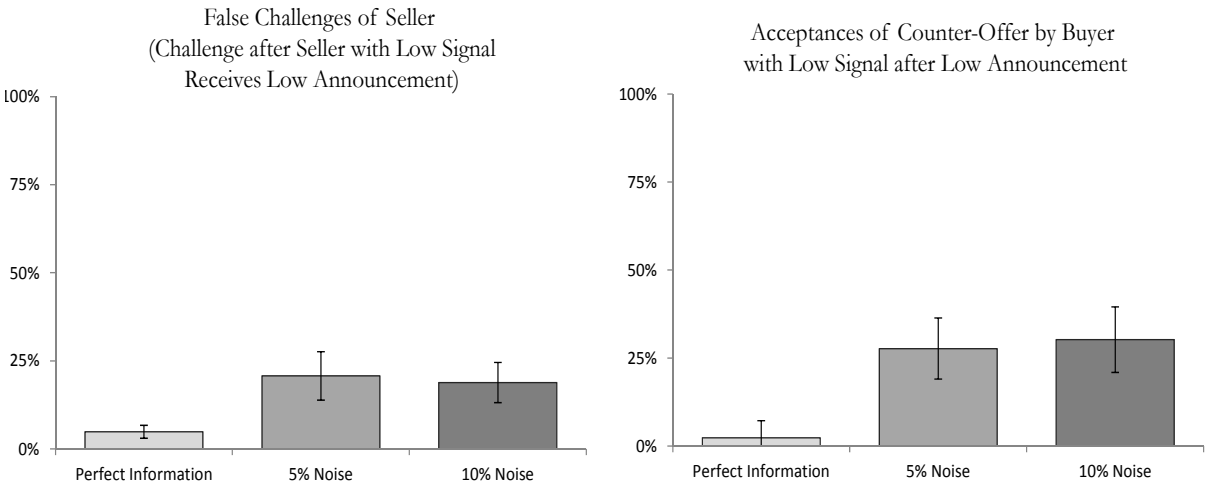


Figure 8: Seller's False Challenges and Buyer's Probability of Accepting a Counter-Offer with Low Signal after a Low Announcement

	Buyer's Average Earnings	**Seller Average Earnings**
No-Noise Treatment	18.9	22.5
5% Noise Treatment	13.8	21
10% Noise Treatment	12.1	21.8

Table 3: Average earnings of the buyer and seller in the last 5 periods of each session. Expected earnings under the truth-telling equilibrium are 22.5 respectively.

challenged. In the no-noise treatment subjects only reach an average surplus of 41.4 which amounts to an efficiency loss of 8%.[24] In the noise treatments the efficiency loss is much higher and amounts to 22.67% in the 5% noise treatment and 24.67% in the 10% noise treatment. Note that these efficiency losses mainly occur because of the imposition of fines to the buyers and the sellers after disagreements, i.e. they represent the direct cost of an imperfectly functioning mechanism. In our setup there are no indirect cost that would arise if the trading parties could invest and an imperfectly functioning mechanism induced inefficiently low investments. Further, even in the absence of indirect costs, it is unclear why trading parties would implement a mechanism involving direct costs if it frequently fails to help them solve their contracting problem by inducing truth-telling.

4.4 Robustness checks

In this section we perform two robustness checks. We have seen in the previous sections that the buyers' frequently believed that their truthful announcements would be challenged with some positive probability, suggesting that these beliefs may have induced the buyers to lie more often. However, the previous evidence on this is correlational, i.e., we did not show that the belief that truthful announcements will be challenged causes the buyers' lying behavior. In section 4.4.1 we tackle this issue of causality. In section 4.4.2 we ask the question whether a further reduction of noise to only 1% imperfect information still causes substantial malfunctioning of the mechanism. If that were the case, even very small amounts of imperfect information would suffice to cause the mechanism to perform poorly.

4.4.1 Does the fear of inappropriate challenges induce buyers' to lie?

If the belief that truthful announcements will be challenged is the main driver of lies in the no-noise treatment and also drives a subset of lies in the noise treatment, then eliminating the potential of such challenges should increase the likelihood of truth-telling in both treatments. We test this hypothesis by running four additional sessions where we eliminated the ability for S to challenge a B who makes a high announcement. Two of the sessions started in the 10% noise treatment and ended in the no-noise treatment while in the other session, individuals started in the no-noise treatment and ended in the 10% noise treatment. This "no-inappropriate challenge" mechanism is expected to increase the expected gain from truth-telling in both the noise and the no-noise treatments. We expect, therefore, that a

[24] The relatively low efficiency costs under perfect information are likely to be due to the fact that we parametrized the experiment such that negative reciprocity is unlikely to play a role. In Fehr, Powell & Wilkening (2014) negative reciprocity induces buyers to reject counteroffers in the majority of the cases which causes the mechanism to be highly inefficient even under perfect information.

large proportion of lies will decrease in this treatment relative to the baseline but that a significant portion of the gap between the no-noise and noise treatments will remain. A total of 82 individuals participated in these additional experiments.

Result 5 *Eliminating the ability of S to challenge high announcements substantially reduces B's lies in both the no-noise treatment and the noise treatment. The introduction of noise leads to an increase in B's lies in both the baseline mechanism and the new mechanism.*

Figure 9 shows the proportion of lies in the original sessions with 10% noise and the new sessions using the no-inappropriate challenge mechanism. The error bars show 95% confidence intervals with standard errors clustered at the individual level. As can be seen, lies in both the noise treatment and the no-noise treatment decrease with the no-inappropriate challenge mechanism as we would expect if pessimistic beliefs about being challenged after a truthful announcement is a major contributor to lying.[25] This decrease in lies is particularly pronounced when comparing the second treatment in each session, where buyer lies fell to only 7.1% in the no-noise treatment and 27.0% in the 10% noise treatment.

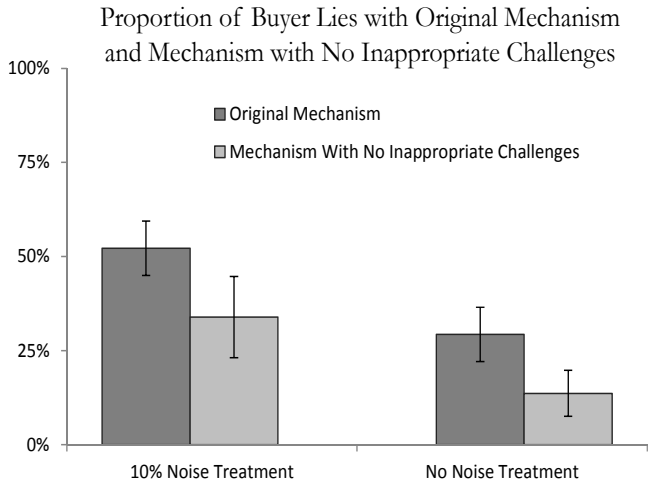


Figure 9: Frequency of Buyer Lies with original mechanism and alternative simple mechanism where high announcements cannot be challenged.

It is interesting to note that the type of sequential mechanism we tested in the above additional sessions is not capable of implementing all social choice functions. Moore (1992) calls mechanisms like this "simple sequential mechanisms" and provides conditions under which they can implement a desired social choice function. Roughly speaking, this requires that only one party has state dependent preferences, or that preferences are perfectly correlated.

[25]The difference in lie frequency between the original mechanism and the no false challenge mechanism is significant at the 10% level based on a Mann-Whitney test where the lie frequency of each individual is the variable of interest: $z = 1.897$, p-value $= .0578$. Similar results hold for a probit regression with data clustered at the individual level ($p = .015$).

4.4.2 How small is small?

While we chose the levels of 5% and 10% noise in order to have enough power to differentiate between treatments, AFHKT suggests that very small levels of noise can lead to a breakdown of the mechanism. To study whether deviations from perfect information impact the distribution of lies even for very small levels of noise, we ran four additional sessions where we started with 10 periods of a 1% noise treatment and ended with a no-noise treatment. A total of 82 individuals participated in these additional experiments. We compare this treatment to the sessions where we started with 10 periods of the 5% noise treatment and ended with a no-noise treatment.

Result 6 *Even a very small perturbation in common knowledge leads to an increase in lies relative to the no-noise treatment.*

Figure 10 shows the proportion of buyer lies and seller false challenges in the 5% noise treatment and 1% noise treatment with 95% confidence intervals clustered at the individual level. The dotted lines in each figure show the proportion of buyer lies and seller false challenges in the subsequent no-noise treatment.

As can be seen in the left hand panel, both the 5% noise sessions and 1% noise have significantly more lies in the noise treatment than in their corresponding no-noise treatment. The proportion of lies in the 5% and the 1% noise treatments is surprisingly similar; there is no significant difference in the proportion of buyer in these two treatments based on a linear regression where buyer lies are regressed on the treatment dummy for the 5% noise sessions ($t = .76$, p-value $= .449$).

As can be seen in the right hand panel, sellers make false challenges 10.3% of the time in the 1% noise treatment relative to 20.8% of the time in the 5% noise treatment — a difference that is just significant ($t = 2.00$, p-value $= .046$) based on a linear regression where sellers' false challenges are regressed on a dummy for the 5% noise treatment.

Taken together, while there is a small reduction in seller false challenges when noise rates decline, the large number of buyer lies in the 1% noise treatment illustrates that even small departures from common knowledge have a significant impact on the willingness of individuals to report truthfully. Our results thus illustrate the non-robustness of the Moore-Repullo mechanism to small amounts of noise.

5 Conclusion

In this paper we conducted a laboratory experiment to test the extent to which Moore and Repullo's subgame perfect implementation mechanism induces truth-telling in practice,

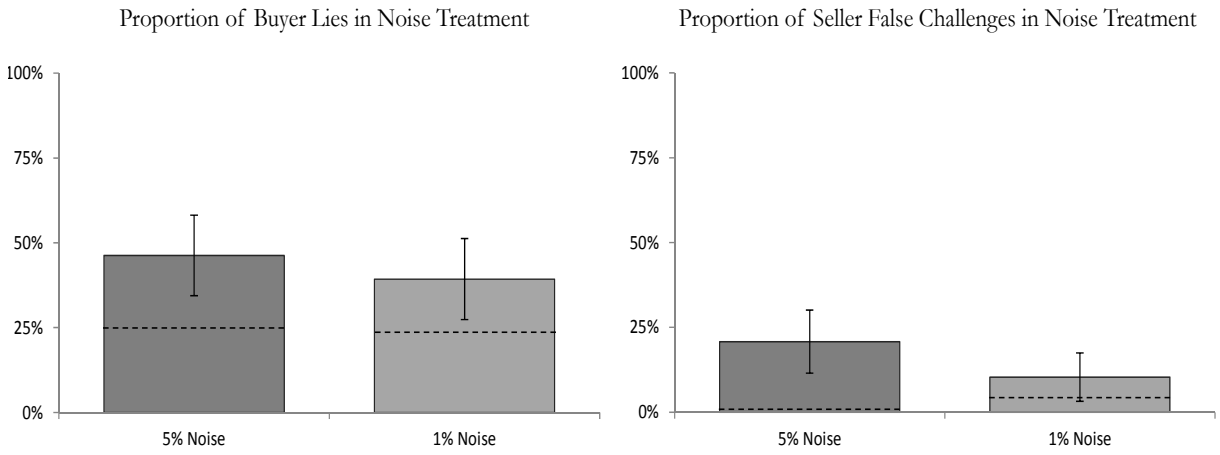


Figure 10: Difference in Lies between Noise and No-Noise Treatments

both in a setting with perfect information and in a setting where buyers and sellers do not share common knowledge about the good's value. Our first finding is that even in the no-noise treatment, where no lies are predicted in equilibrium, buyers lie by announcing a low value with a high signal roughly 25% of the time. Our data suggests that in all treatments a substantial proportion of these lies are driven by pessimism about being inappropriately challenged after a high announcement. This pessimism is strong enough that a large majority of individuals who are telling the truth believe they would be better off lying, which suggests that the mechanism is being supported in part by non-pecuniary incentives for telling the truth.

Our second main finding is that the introduction of noise leads to an increase in buyers' lies and sellers' false challenges in a way consistent with the analysis in AFHKT. The introduction of noise increases the proportion of buyers who announce a low value with a high signal by 15 to 25 percentage points; these lies are persistent and do not diminish with experience. Similarly, the proportion of sellers who falsely challenge in the noise treatments increases by 15 percentage points relative to the no-noise treatment. Lack of perfect information is behaviorally important even when the level of noise is reduced to a very small 1% level.

If we adjust the Moore-Repullo mechanism by ruling out false challenges, buyers' lying rate in the no-noise treatment decreases by 15.6 percentage points. Likewise, the institutional removal of such false challenges also decreases the lying rate in the noise treatments significantly. However, in the noise treatments this deviation from the Moore-Repullo mechanism does not solve the lying problem. Even if the fear of false challenges of high announcements is ruled out, a lying rate of 27% prevails in the 10% noise treatment, which indicates the

pervasive influence of uncertainty regarding the good's value on lying behavior.

One important potential objection to our findings is that when parties themselves design a mechanism one should be less concerned about the fears of irrationality that play a prominent role in our experiment. As Eric Maskin suggested to us, when the parties are designing a contract they may engage in all sorts of discussion about how the game might be played. This is an important point to which we have two responses. First, pre-play communication can naturally be modelled as a cheap-talk stage prior to the mechanisms studied in this paper. To understand the benefits or otherwise of such communication one should, and can, model this additional stage. Second, pre-play communication does not obviate the fact that in our setting, players observe conditionally independent signals, and thus higher-order beliefs are relevant to play in the game induced by the mechanism. The fact that the players in the game designed the game itself does not alter the fact that common knowledge of the underlying state — something that is not a design variable — is crucial to the success of the mechanism. That said, understanding how pre-play communication intersects with the issues studied in this paper is an enticing avenue for both theoretical and experimental work.

Our findings suggest several important avenues for future research, in addition to that mentioned in the preceeding paragraph. First, the fact that individuals are willing to sacrifice their material well-being to tell the truth suggests that preferences for honesty should help implementation.[26] Second, in view of the empirical relevance of common knowledge, it also is important to design mechanisms that are robust to at least small amounts of imperfect information about the good's value. Third, it would be interesting to know (theoretically and empirically) how the introduction of asset ownership affects the functioning of extensive form mechanisms. In particular, asset ownership could be naturally modeled as an outside option for the asset holder, which in turn would affect either party's incentive to report the good's value truthfully or to challenge the other party. It would be interesting to see whether asset ownership helps achieve better equilibrium outcomes that are also robust to introducing small amounts of private information. Finally, similar experiments could be used to test the robustness of other implementation mechanisms, starting with virtual implementation. Overall, our analysis and findings in this paper raise a number of exciting issues to be tackled by future research.

[26] Current research by Kartik, Tercieux and Holden (2014) suggests that when individuals have a known preference for honesty, full implementation can be achieved with simple mechanisms requiring only two rounds of iterated deletion of strictly dominated strategies.

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Appendix A: Point Predictions of the Mixed Strategy Equilibrium

As in the main text, let the true valuation of the good be $\theta \in \{\theta^H = 70, \theta^L = 20\}$, with both states being equally likely. Let each player receive one of two possible signals, s^H and

s^L, where s^H is a high signal correlated with θ being equal to 70, and where s^L is a low signal correlated with θ being equal to 20. Using the notation s_B^H (resp. s_B^L) to indicate that B received the high signal s^H (resp. the low signal s^L), the following table shows the joint probability distribution ν^ε over θ, the buyer's signal s_B, and the seller's signal s_S :

ν^ε	s_B^H, s_S^H	s_B^H, s_S^L	s_B^L, s_S^H	s_B^L, s_S^L
$\theta = 70$	$\frac{1}{2}(1-\varepsilon)^2$	$\frac{1}{2}\varepsilon(1-\varepsilon)$	$\frac{1}{2}\varepsilon(1-\varepsilon)$	$\frac{1}{2}\varepsilon^2$
$\theta = 20$	$\frac{1}{2}\varepsilon^2$	$\frac{1}{2}\varepsilon(1-\varepsilon)$	$\frac{1}{2}\varepsilon(1-\varepsilon)$	$\frac{1}{2}(1-\varepsilon)^2$

For a given noise level ε, an action profile of a buyer consists of a probability of announcing low after observing each signal and a probability of rejecting the challenge given a signal and an announcement. Denote L^H as the probability of making a *low* announcement after observing a high signal and L^L as the probability of making a low announcement after a low signal. Further, let $R^{a_B|s_B}$ be the probability that the buyer rejects a challenge given his own announcement $a_B \in \{L, H\}$, his own signal $s_B = \{L, H\}$ and a challenge by the seller.

An action profile of the seller consists of a probability of challenging an announcement of the buyer for each potential announcement and signal. Let $C^{a_B|s_S}$ be the probability that the seller challenges given signal $s_S \in \{L, H\}$ and an observed announcement of the buyer $a_B = \{L, H\}$.

While there are 10 potential mixing probabilities to specify in an equilibrium, we can use some of the structure of the mechanism to rule out mixing on some action sets. Let $P_{20} = 10$ and $P_{70} = 35$ be the trade prices without arbitration and let $P_A = 25$ and $P_B = 75$ be the counter-offer prices after announcing 20 and 70. A buyer who announces high and is challenged faces a price of $P_B = 75$ which is above his actual value of the good regardless of the state. Thus the buyer will always reject arbitration if he has announced high and $R^{H|L} = R^{H|H} = 1$. This also implies that the seller will never call the arbitrator if the buyer announces high, and thus $C^{H|L} = C^{H|H} = 0$. Further, a buyer who has a high signal and announces low will update his belief about the quality of the good based on the act of being challenged by the seller. However, for any equilibrium where the seller challenges with positive probability, the most pessimistic posterior the buyer can have after being challenged is that the state is low with probability 1/2 (The posterior in the unlikely case where the seller challenges only with the low signal). As the counter-offer price is 25 and the buyer's expected value for the good with this belief is 45, the buyer will always accept the counter-offer, and thus $R^{L|H} = 0$. Finally, the best a buyer can do with a low signal if he always announces high is to receive 35 with probability ε and -15 with probability $1 - \varepsilon$. If in equilibrium the buyer earns more than $35\varepsilon - 15(1 - \varepsilon)$ for a low announcement, it will be

the case that $L^L = 1$.[27]

Taking as given the actions of buyers and sellers in the six states specified above, the mixed strategy equilibrium is based on (i) the proportion of times a buyer announces low given a high signal, L^H, (ii) the challenge probabilities given a low announcement, $C^{L|L}$ and $C^{L|H}$, and (iii) the probability that the buyer rejects a challenge given a low signal, a low announcement, and a challenge, $R^{L|L}$. These four mixing probabilities form the basis of all PBE where all stages of the subgame are reached and beliefs of both parties are consistent with the action profiles of the other party.

Given that beliefs of all parties must be consistent with their actions, a necessary condition for the mixed strategy equilibrium is that each individual is indifferent between each of their actions given the mixing probabilities of the other parties. These indifference conditions generate four linear constraints on the four mixing probabilities of the buyer and seller and generate a four-by-four linear system which derives unique point predictions. The construction of each linear constraint is as follows:

(1) Buyer's indifference between announcing low and high with a high signal: For the buyer to be indifferent between announcing high and low, the expected value of these announcements must be equal when aggregated over all potential states of nature.

Panel (a) of Figure 11 shows the four potential states of nature where the buyer can have a high signal after nature draws the true value of the container and (conditional) signals for the buyer and seller. For each state, the expected value of each potential announcement is shown as a function of the challenge probabilities of the seller. For example, as seen on the far left of the figure, with probability $\frac{1}{2}\varepsilon(1-\varepsilon)$, the buyer receives the high signal, the seller receives the low signal, and the true state of nature is low. If in this state the buyer announces low, he will not be challenged $1-C^{L|L}$ percent of the time and be challenged $C^{L|L}$ percent of the time. As he has the high signal, he will always accept the counter-offer and thus these two outcomes yield values of $20 - P_{20} = 10$ and $20 - F - P_A = -30$ respectively. If, on the other hand, the buyer announces high, he will never be challenged (since $C^{H|L} = 0$) and receive $20 - P_{70} = -15$ for sure.

Taking into account the probability of each one of these potential states and the state's outcome, a buyer is indifferent between a high and low announcement if:

$$\psi(\varepsilon)C^{L|H} + \delta(\varepsilon)C^{L|L} = \frac{P_{70} - P_{20}}{F + P_A - P_{20}}, \tag{4}$$

Where $\psi(\varepsilon) = \varepsilon^2 + (1-\varepsilon)^2$ is the probability that the signals are the same for a given ε and

[27] We argue in the main text that there is a pure strategy equilibrium where $L^L = 0$ and challenges never occur.

$\delta(\varepsilon) = 2\varepsilon(1-\varepsilon)$ is the probability that they are different.

(2) Buyer's indifference between accepting and rejecting a challenge with a low signal and low announcement: In an equilibrium in which the seller is mixing between challenging and not challenging a low announcement with a low signal, it must be the case that the buyer is also indifferent between rejecting and accepting such a challenge. Panel (b) of Figure 11 shows the probability of reaching this acceptance and rejection as a function of the signals and the challenge probabilities of the seller and under the assumption that $L^L = 1$. Taking into account the probability of each of these potential states and the state's outcome, a buyer is indifferent between rejecting and accepting the challenge if:

$$C^{L|L} - \tau(\varepsilon)C^{L|H} = 0, \tag{5}$$

where

$$\tau(\varepsilon) = -\frac{\varepsilon(1-\varepsilon)[70 - P_A] + (1-\varepsilon)\epsilon[20 - P_A]}{\varepsilon^2[70 - P_A] + (1-\varepsilon)^2[20 - P_A]} \tag{6}$$

is the ratio of expected outcomes when the two parties have opposite signals relative to when they have the same signal. Note that $\tau(\varepsilon)$ is positive for all ϵ we consider since the denominator is negative.

(3) Seller's indifference between challenging and not challenging after a low signal: As with the buyer, the seller's indifference for challenging after a low and high signal are based on the two mixing probabilities of the buyer. Panel (a) of Figure 12 shows the expected value for challenging and not challenging for states of the world where the seller has a high signal and observes a low announcement. The likelihood of reaching each of these potential states is based on the likelihoods that the buyer will make a low announcement with each signal (L^H and $L^L = 1$) while the expected value of challenging is based on the likelihood that the buyer will accept this challenge ($R^{L|L}$ and $R^{L|H} = 1$). A seller is indifferent to challenging and not challenging with the high signal if:

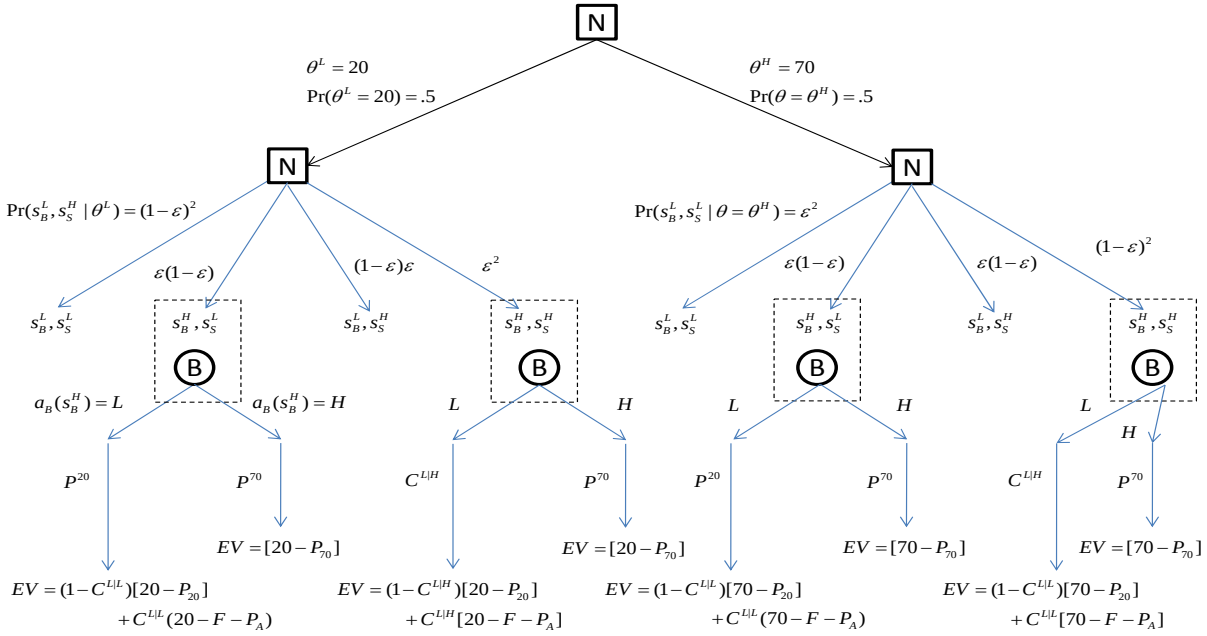
$$-L^H + \frac{\delta(\varepsilon)}{\psi(\varepsilon)}\frac{P_A + 2F}{P_A + F - P_{20}}R^{L|L} = \frac{\delta(\varepsilon)}{\psi(\varepsilon)} \tag{7}$$

where, as before $\psi(\varepsilon) = \varepsilon^2 + (1-\varepsilon)^2$ is the probability that the signals are the same for a given ε and $\delta(\varepsilon) = 2\varepsilon(1-\varepsilon)$.

(4) Seller's indifference between challenging and not challenging after a high signal: Panel (b) of figure 12 shows the expected value for challenging and not challenging for states of the world where the seller has a low signal and observes a high announcement. As before, the seller's likelihood of reaching each potential state depends on L^L while the expected value

Figure 11: States Contributing to the Decision of the Buyer to Lie and Reject a Potentially False Challenge

(a) The four potential states that contribute to the buyer's decision to lie by announcing low with a high signal. The outcomes of these states are shown for a low and a high announcement.



(b) The four potential states which contribute to a buyer's decision to accept or reject a potentially false challenge. The outcomes of these states are shown for a rejected and an accepted counteroffer.

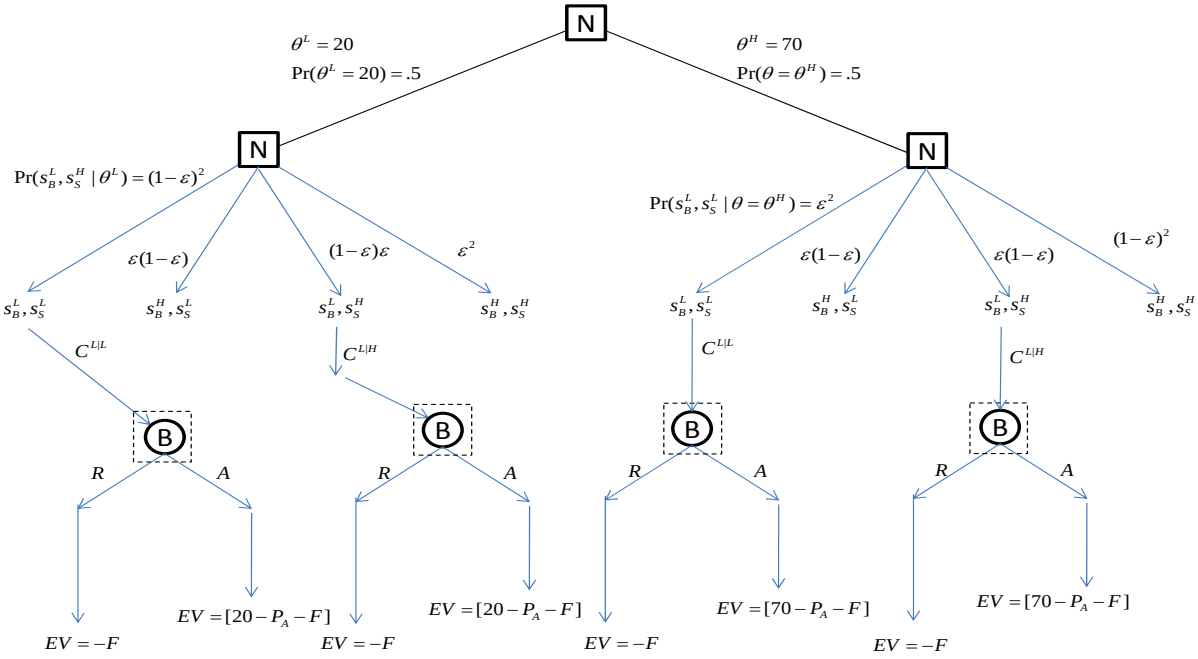
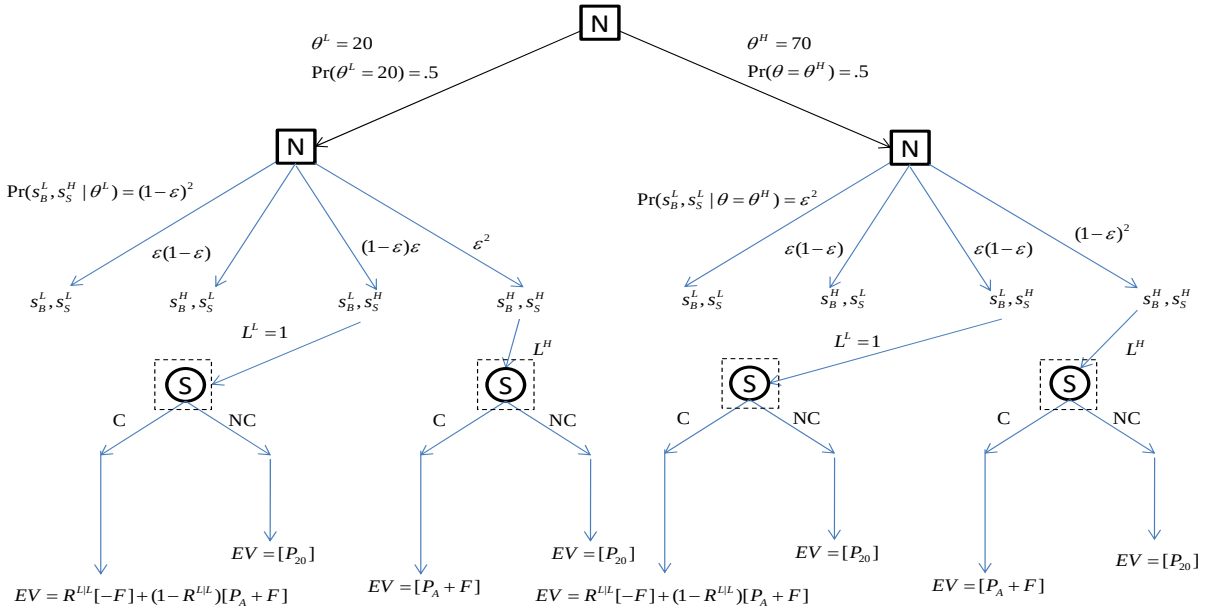
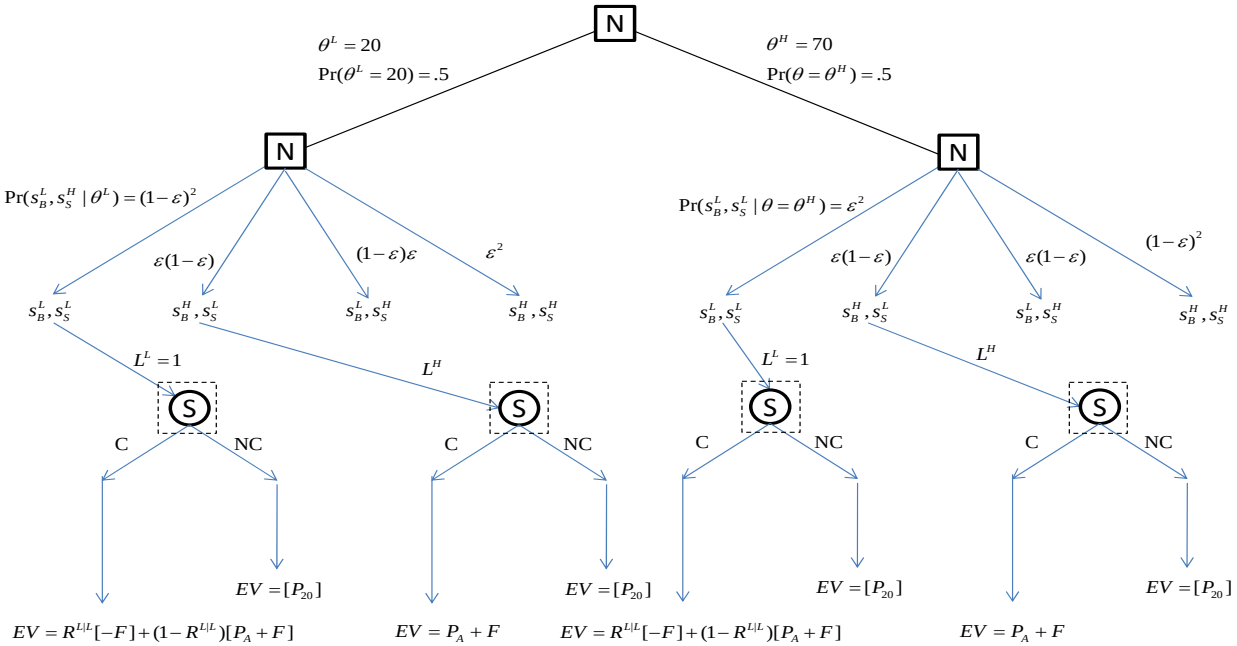


Figure 12: States Contributing to the Decision of the Seller to Challenge with a High and Low Signal

(a) The four states which contribute to a seller's decision to challenge a low announcement when observing a high signal. The outcomes of these states are shown in the case of a challenge and no challenge



(b) The four states which contribute to a seller's decision to challenge a low announcement when observing a low signal. The outcomes of these states are shown in the case of a challenge and no challenge



within these nodes depends on $R^{L|L}$. A seller is indifferent to lying and not lying if:

$$-L^H + \frac{\psi(\varepsilon)}{\delta(\varepsilon)} \frac{P_A + 2F}{P_A + F - P_{20}} R^{L|L} = \frac{\psi(\varepsilon)}{\delta(\varepsilon)}. \tag{8}$$

Note that this is identical to the seller's indifference condition for challenging with the low signal except that the ratio of states is inverted.

Given the four indifference conditions, the point predictions of the model come from solving the four-by-four system of simultaneous equations. The solution to this system is as follows:

Result 7 *With selfish agents, the mixed strategy equilibrium with* $\varepsilon = .05$ *is* $L^H = 0$, $R^{L|L} = .53333$, $C^{L|H} = .66$, *and* $C^{L|L} = .285$. *The mixed strategy equilibrium with* $\varepsilon = .1$ *is* $L^H = 0$, $R^{L|L} = .53333$, $C^{L|H} = .625$, *and* $C^{L|L} = .625$.

The surprising restriction that $L^H = 0$ is due to the fact that the seller must be indifferent to mixing in the case of a high and low signal.

Appendix B: Mechanism used to elicit incentive compatible beliefs

In the follow-up treatment with incentive compatible beliefs, we use the following belief elicitation game based on a mechanism developed by Karni (2009). For each potential combination of announcement and signal, buyers are asked to submit a belief, b, between 0 and 100 corresponding to the percentage chance that the seller will call in the arbitrator. A random number $c \in [0, 100]$ is then drawn by the computer which corresponds to the "computer's percentage chance of calling in the arbitrator."

At the end of the experiment, one of the periods is randomly selected for payment. Using an eight-sided dice, the main experiment is paid 50% of the time while each of the four potential beliefs are paid 12.5% of the time. If a belief elicitation game is selected, the belief elicitation game is resolved as follows. If $b \leq c$ the buyer is matched with the seller and his outcome is based on the arbitration decision of the seller. If the seller does not call the arbitrator, the buyer receives \$20. If, however, the seller calls the arbitrator, the buyer receives \$0. If $b > c$, the buyer is matched to the computer. The computer calls the arbitrator with probability $c/100$ and thus the buyer receives \$20 with probability $1-(c/100)$ and \$0 otherwise.

The mechanism is similar to the Becker, DeGroot, Marshack (1964) mechanism and is shown by Karni (2009) to induce truthful reporting of beliefs for rational agents with any

von Neumann-Morgenstern utility function. Further, as individuals are paid only for the main experiment or the bonus game, there is no concerns about hedging. The mechanism and payment scheme are thus robust to heterogeneity in risk aversion and are incentive compatible.

As the belief elicitation mechanism is relatively complex, we provide extensive training with the mechanism before the start of the experiment. Buyers receive both written and oral instructions about the mechanism, which include a series of examples that make clear that under reporting or over reporting beliefs can lead to worse outcomes. Subjects are also told explicitly that it is best to write down their true belief. Following the instructions, subjects are also given a series of quiz questions about the elicitation mechanism where they must calculate various potential outcomes for truthfully reported and misreported beliefs.