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Does competition affect truth-telling? An experiment with rating agencies

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Abstract

We study the effect of competition on the conflicts of interest in an issuer-pay model. Our analysis complements the theoretical work of Bolton, Freixas and Shapiro (2012) by introducing an experimental approach that examines the effect of market structure –monopoly and competition– on the incidence of misreporting by rating agencies. In our game, agencies receive a signal regarding the type of asset that the seller holds. The seller does not know the asset type and therefore, asks the rating agency for a report which is either blue (good) or red (bad). The asset, along with the report (if any), is then presented to the buyer for purchase. We find that in the monopoly environment the likelihood of misreporting is almost three times as high as in the more competitive market.

Keywords: Credit rating agencies, Conflicts of interest, Market structure, Laboratory experiment

JEL codes: C91, D43, D82, G24, L15

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1 Introduction

Following the financial crisis of 2008, the Financial Crisis Inquiry Commission wrote that many failures within the financial markets could be attributed to the fact that "major firms and investors blindly relied on credit rating agencies as their arbiters of risk." Such heavy reliance on reports by investors is problematic when we consider the inherent conflict of interest that exists between those who pay for the reports (issuers of debt) and those who produce them (the credit rating agencies or CRAs hereafter). Therefore, it is not surprising that the legislature following the financial crisis, the Dodd-Frank Wall Street Reform and Consumer Financial Act of 2010, contains a section meant to improve the regulation of CRAs and increase investor protection (Title IX, Subtitle C).

To become a CRA, U.S. regulations mandate special accrediation by the government as a "nationally recognized statistical rating organization" or a NRSRO. As of 2014, there are currently ten such companies in existence, with three of them (Moody's, Standard & Poor's and Fitch) controlling 95 percent of the market. Over the past few decades, the actual number of NRSROs varied considerably, falling to six in the 90s and then rising again.[1] In the wake of financial crisis, where much of the blame was placed upon the presumably unscrupulous actions of the CRAs, the European Parliament began to advocate for an increase in competition in the CRA market.[2]

In this paper, we propose and conduct an experiment to analyze the effect of increased competition on the CRA market. Using an experimental approach has a number of advantages. We can control the environment of our participants and vary a number of parameters, allowing us to isolate and determine key factors (such as market competition) that influence behavior. Furthermore, the laboratory environment is unique because it allows us to measure factors that are not readily observable through empirical methods. For example, we can estimate buyer sophistication, and observe directly whether any CRAs are misreporting. In turn, this permits us to determine when rating inflation is sustainable, and when it is not.

To study the variation in inflation across market formats, we use the theoretical framework of Bolton, Freixas and Shapiro (2012) –BFS12 hereafter. The authors suggest three potential sources of conflicts: (i) the CRAs desire to understate risk in order to attract business, (ii) the ability of sellers to purchase the most favorable ratings, and (iii) buyer sophistication. According to the model, these conflicts then result in two distortions: (i) reduction in efficiency due to ratings shopping and (ii) higher ratings inflation during booms.[3]

[1] White (2010) provides and excellent overview of how financial regulatory structure affected behavior of rating agencies by increasing their market power via legislature that established NRSROs and also discusses the change from investor to issuer pay model currently in use.

[2] http://www.europarl.europa.eu/news/en/news-room/content/20111219IPR34550/html/Credit-rating-agencies-MEPs-want-less-reliance-on-big-three

[3] Using an experiment without an intermediary (CRA), Kluger and Slezak (2015) find that misreporting

Although we closely follow the work of BFS12, our design does differ in few ways. We allow for only one report to be purchased in the competitive treatment, and instead of the seller posting the terms, we have buyers bid for the assets. We believe that allowing buyers to bid based on reports available (or lack of) can provide a better approximation of how naive or trusting the buyers are. Our findings suggest that inflation is costlier when the market is competitive. In fact, our estimations show that in the monopoly treatment the odds of misreporting are 3.7 higher than in the competitive treatment. Further, our results indicate a level of sophistication among buyers since their bids differ according to the presence and absence of reports.

A common concern, as cited earlier, in a competitive CRA market is "ratings shopping." That is, an issuer of debt (a seller) is not required to accept a report that he does not like. Therefore, if one CRA issues a negative report, the seller can search, or essentially shop, for a better one. Faure-Grimaud, Peyrache, and Quesada (2009) find that increased competition between CRAs results in less information disclosure.

However, competition can also drive down the fees charged by the CRAs, making inflation costly. Bar-Isaac and Shapiro (2013) find that ratings are less-accurate when fee-income is high, using a theoretical model with endogenous reputation. Therefore, if competition puts a downward pressure on fees, then inflation and ratings shopping would be less likely to occur. In another theoretical work, Manso (2013) finds that increased competition leads to rating downgrades (tougher ratings), increased default frequency and reduced welfare. Furthermore, he suggests that the CRAs should consider long-term borrower survival, which means that soft-rating equilibirum (higher ratings) may be preferable. Thus, while an increase in competition can make rankings more accurate, such outcome is not necessarily preferably if it decreases the odds of survival of the firms.

Using an evolutionary approach, Hirth (2014) analyzes CRAs and competition, where investors are either sophisticated or naive. He finds that CRAs can be honest when there are enough sophisticated investors in the market, so that reputational concern is real. In our experimental design, and given our parameter values, the necessary minimum level of naive investors to make inflation feasible is about 72 percent. Furthermore, Hirth determines that there is a critical number of CRAs in the market, above which the reputation costs become high enough to guarantee at least temporary honest behavior.

Becker and Millbourn (2011) use an empirical approach to show that an increase in competition due to the entrance of Fitch to the ratings market, actually leads to lower quality ratings from the incumbents. The quality was measured via two dimensions here: (i) the ability of ratings to transmit information to investors and (ii) the ability of ratings

is more likely to occur during busts. One possible explanation is that sellers have different incentives to misreport during booms and busts, while trusting behavior of buyers does not change over the business cycle.

to classify risk. Another recent empirical work of Baghai, Servaes and Tamayo (2014) analyzes the changes in standards of the CRAs over time. They find that for corporate debt, CRAs have actually become more conservative. That is, according to the results, a AAA firm from 1985 would be rated AA today.

On the other hand, Cole and Cooley (2014) argue that the problem is not who pays for the ratings because reputational concerns insure this. The real issue, according to the authors, is that regulatory reliance on ratings and the increasing importance of risk-weighted capital in regulation leads to distorted ratings. Information distortion exists because those who purchase the ratings do not necessarily need to reveal them.

The ultimate impact of ratings provides by the CRAs is actually quite complex. According a to a number of studies, ratings have a dual role: they provide information to investors and they are used for regulatory purposes (Kisgen and Strahan, 2010; Ashcraft, et al., 2010). Therefore, ratings can affect market price through regulation, independent of the information they provide about the actual asset. In turn, rating contingent regulation increases the volume of highly rated securities (Opp, Opp and Harris, 2013).

As far as experimental literature, perhaps the closest work is by Mayhew, Schatzberg and Sevcik (2001), who examine whether accounting uncertainty (signal precision) impacts auditor objectivity. The results of this study suggest that accounting uncertainty impacts auditor objectivity despite the damage to auditor reputation and that in the absence of uncertainty auditors remain objective. In a subsequent study extending the 2001 design, Mayhew and Pike (2004) analyze whether investor selection of auditors can improve auditor independence and find that transferring the power to hire and fire the auditor from managers to investors significantly decreases the proportion of violations and increases the overall economic surplus.[4]

Other important experimental work that can help understand the dynamics of the CRA market deals with sender-receiver games and cheap talk. Forsythe, Lundholm and Rietz (1999) study a market where only sellers know the true value of the asset. When cheap talk is allowed, they find that sellers make fraudulent announcements 47 percent of the time (with standard deviation of 19). Similarly, Sheremeta and Shields (2013) find the receivers prone to deception. In a study where subjects play both roles, they find that in the role of the sender, the majority of subjects adopt deceptive strategies (60 percent) by sending favorable message when the true state of the nature is unfavorable. As receivers, nearly 70 percent of the subjects invest when the message is favorable.[5] Adding a competition aspect to the sender-receiver game, Cassar and Rigdon (2011) find that including an additional

[4]Moore, Tetlock, Tanlu and Bazerman (2006) focus on the morality behind rating inflation and propose a number of strategies to reduce the conflict of interest, such as hiring CRAs long term regardless of their reports.

[5]The authors note that investment behavior of receivers cannot be explained by risk preferences or as a best response to the subject's own behavior in the sender's role.

sender increases trust and trustworthiness. However, this outcome requires an environment of complete information.

In addition to laboratory experiments, there are also field experiments that consider the role and impact of CRAs. Duflo, Greenstone, Pande and Ryan (2013) conduct a randomized field experiment that provides evidence on how conflict of interest undermines information provision by third-party auditors. The results show that a set of correct incentives or reforms can lead to greater accuracy and improve compliance with regulation.

To control cheating, or inflation, we can introduce punishment, change market format, include reputation cost, or add some other mechanism with the hope of realigning player incentives. Some studies have already looked at punishment (Sánches-Pagés and Vorsatz, 2007) and while others included reputation costs in the analysis, both endogenously or exogenously (Mayhew, Schatzberg and Sevcik, 2001; Mayhew and Pike, 2004; BFS12). We introduce competition and provide experimental evidence whether it is an important factor in mitigating conflicts of interest that are partially blamed for the financial crisis of 2008.[6]

The rest of the paper is organized as follows: section 2 describes the general environment of the credit ratings game, section 3 details the laboratory procedures, section 4 presents the results and lastly, section 5 discusses our main findings. Appendix A includes instructions used in experimental sessions and Appendix B shows the screenshots of the user-interface.

2 The environment

The environment in our experiment closely follows the work of BFS12 and studies the interaction of three player types: sellers, CRAs and buyers. Although the model specifies one seller, many buyers and either one or two CRAs, for the purposes of our experiment, we constrain the number of buyers to two. In the market, there are two types of widgets that can be sold, either blue (b) or red (r), $\omega \in \{b, r\}$. A buyer's valuation for each widget type is summarized by V_r and $V_b > V_r$. Ex ante, the buyer does not know the type of widget is sold in the market. However, the buyer may have access to a report, suggesting widget type, if the seller chooses to purchase it from the CRA.

The CRA has access to a research team which receives an informative signal regarding

[6]We should also consider if truth-telling is really the desired behavior, and that depends on what we consider to be the better outcome. According to Cassar, Friedman and Scneider (2009), cheating faciliates trade by increasing the overall volume, though it also decreases cross-market trade significantly. In their environment, contracts can only be enforced domestically (cheating is not possible) but not internationally (cheating is possible). This causes high surplus traders to leave international markets for domestic ones.

widget type $\theta \in \{bb, rr\}$. The private signal has the following informational content ω,

$$\Pr(\theta = bb|\omega = b) = \Pr(\theta = rr|\omega = r) = e > 1/2$$

where $e \in (\frac{1}{2}, 1)$ is the precision of the signal. In our experiment we allow for high precision so that $e = 0.90$.[7]

Prior to receiving the signal, the CRA must post a fee ϕ at which a report can be purchased by the seller. When the seller approaches the CRA, it retrieves a signal θ and produces a report. The CRA does not have to report the signal suggested by the research team. After reading the report, the seller can either accept the report (and pay ϕ) or reject it (CRA receives zero). In this environment it is not possible to have unsolicited ratings, therefore when a report is rejected by the seller, the buyer must guess or deduce the value of the widget.

The published report (if any) is a message suggesting widget type, $m = bbb$ ("blue") or $m = rrr$ ("red"), that is observable to buyers. The agency also has a fixed endowment ρ, which is lost in the case that the report is *bbb*, given that the research team announced *rr* and the widget is *r*. The endowment can be considered an exogenous reputation cost, cost of litigation, or any cost associated with the consequence of distributing a purposefully inaccurate or inappropriate information to market participants.

The buyers observe a report, if published, and then bid for the widget. The profits for each player are then computed as follows

$$\pi^{\text{buyers}} = \begin{cases} V_\omega - bid & \text{if winning bid} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$\pi^{\text{agencies}} = \begin{cases} \rho + \phi & \text{if report is truthful and is published} \\ \phi & \text{if report is not truthful and the state is red} \\ \rho & \text{if report is rejected} \end{cases} \tag{2}$$

$$\pi^{\text{sellers}} = \begin{cases} bid - \phi & \text{if report is accepted} \\ bid & \text{otherwise} \end{cases} \tag{3}$$

BFS12 also assume that there are different types of buyers, which we account for with the constant $\alpha \in [0, 1]$. The type $\alpha = 1$ bids the highest possible valuation regardless of the report received, while type $\alpha = 0$ processes information rationally and bids according to message received. Therefore, α can be interpreted as the fraction of either naive, trusting,

[7]Mayhew et al. (2001) study the impact of signal certainty on objectivity of auditors and find that there are less violations when signal is more precise.

or less sophisticated buyers. We define the value of the widget for type $\alpha = 0$ as

$$\begin{aligned} W^b &= (1-(1-e))V_b + (1-e)V_r \\ W^r &= (1-e)V_b + (1-(1-e))V_r \\ W^0 &= (1/2)V_b + (1/2)V_r \end{aligned}$$

The theoretical predictions in a monopoly environment suggested by BFS12 are summarized in Proposition 1.

Proposition 1 *The two resulting equilibria of the game are*

1. *The rating agency always reports blue (bbb). Inflation occurs as long as the fee satisfies the following condition $\phi = \alpha W^b - W^0 > e\rho$.*

2. *The rating agency reports truthfully. This results in a fee such that $\phi = \min[W^b - \max[\alpha W^0, W^r], e\rho]$*

Which equilibrium do we expect in our experiment? We know that in sender-receiver games truth-telling is fairly common and highly variable (Forsythe, Lundholm and Rietz, 1999; Sánches-Pagés and Vorsatz, 2007).[8] When deception occurs, it does so at the expense of other players who are trusting (Sheremeta and Shields, 2013; Hirth, 2014). We also know that inflicting harm on the other party does not seem to factor in the decision to deceive (Gneezy, 2005; Hurkens and Kartik, 2009).[9] Therefore, we would not be surprised to see a significant amount of truth-telling develop over the course of the game.

Aside from the monopolistic case, we also analyze the effect of competition in the CRA market. We deviate from the model proposed by BFS12 by restricting the seller choices. Specifically, we limit the seller to accept only one report, whereas BFS12 allow the seller accept both, and therefore their theoretical analysis accounts for the value of the additional report. In our simiplified environment where only one report is allowed in the market, the seller can accept one or reject both. The CRA market can thus be characterized as a Bertrand competition where firms simultaenously set prices and compete to sell undifferentiated products.

In the competitive treatment we expect the equilibrium predictions to be similar for most part. However, we also expect that the fees charged by the CRAs will be lower due to competition. If competition drives the CRA fees below the cost of inflation, then it will

[8] Sánches-Pagés and Vorsatz (2007) also find that punishment only minimally increases truth-telling. On the other hand, truth-telling can also be viewed as deceptive if the sender chooses the true message with the expectation that the receiver will behave in a way contrary to the message (Sutter, 2009).

[9] Gneezy (2005) suggests that truth-telling may be linked to wanting to avoid harming the other party. However, Hurkens and Kartik (2009) do not find vidence to support this notion.

become optimal to report truthfully. A priori, it is difficult to determine how much the fees will decrease. In part, that depends on buyer sophistication. If α is high enough, then the value of blue report is higher, which should increase fees and inflation. In this case, we may be also need to be concerned about ratings shoppings (see BFS12, Cantor and Pack, 1994). Experimental data should provide additional insight on factors driving the decision to inflate.

Given what we know from past literature and overall market dynamics, we narrowed down our predictions to the following:

Prediction 1 *Lack of a report is viewed similar to a red report if the buyers are sophisticated.*

Prediction 2 *The fee when the rating agency inflates is greater than $e\rho$.*

Prediction 3 *In the monopoly treatment, inflation appears, but it is not dominant.*

Prediction 4 *The fee under competition is lower than in the monopoly treatment.*

For the purposes of the experiment, we assume the following parameter values: $V_b = 120$, $V_r = 20$, $e = 0.9$, and $\rho = 10$. These parameters result in the following expected widget values: $W^b = 110$, $W^0 = 70$ and $W^r = 30$. These outcomes are based on the the 90 percent signal accuracy when the CRA is truth-telling.

Buyer sophistication parameter, α, plays an important role in the realization of the equilibria predicted by BFS12. Under our parameter values, the minimum value of α that makes the BFS12 inflation equilibrium feasible is $\alpha^* = 0.72$. That is, we need a large fraction of naive or trusting buyers. Anytime that $\alpha < \alpha^*$, rational buyers will assume that a high fee indicates inflation by the CRA and will bid low.

3 Laboratory Procedures

We employed a total of 144 subjects in 16 pits at the CEED laboratory in Ball State University between February and April 2015. Participants, who include undergraduate students from all fields and were recruited online via ORSEE (Greiner, 2004) and we assigned to the role of either sellers, CRAs or buyers. The treatments are designed to analyze the forces of competition on the behavior of rating agencies. We run a completely between subject-design, with each experimental session consisting of either one or two independent pits. The term pit refers to markets formed by buyers, sellers and credit rating agencies.

Table 1 presents an overview of the sessions conducted.

Table 1: Session overview and number of observations

Treatment	Variable	Sellers	Rating agencies	Buyers
Monopoly	Count	16	16	32
	Average profit ($)	13.0	9.9	8.3
	Average show-up fee ($)	5.4	5.3	8.3
Competition	Count	16	32	32
	Average profit ($)	12.4	8.5	8.7
	Average show-up fee ($)	5.4	5.8	7.3

Note: Each pit has two sellers, four buyers and depending on treatment, either two or four rating agencies. That is, we have 8 pits in each treatment and 16 possible market transactions.

In the monopoly treatment, we have a pit with two sellers, two CRAs and four buyers that is split into two groups. These two groups are then reshuffled every period for a total of 24 periods so that each resulting group formation is unique. In the competitive treatment, the number of CRAs is increased to four in each pit, while the number sellers, buyers and periods remains constant.

In the monopoly treatment, every session proceeds as follows:

Stage 1: CRA enters the fee that it would like to charge for writing the report. Figure 1 in Appendix B shows the user interface of Stage 1, designed in Ztree (Fischbacher, 2007).

Stage 2: CRA receives information from the research team, i.e. an informative signal, regarding the value of the widget (red or blue) and then selects whether to report red or blue.

Stage 3: The seller observes the color reported and the fee posted by the CRA and decides whether to accept the report.

Stage 4: Buyers observe the report (either blue or red), if any, and the fee paid associated with the report. Buyers then bid for the widget, which can be any value between zero and 120.

Final stage: Profits are computed using equations (1-3). All players observe whether the CRA lost the endowment for misreporting a red signal as blue when the state turned out to be red.

The information displayed to all players includes the value of the widget in a blue state, red state, and the accuracy of the research team (90 percent). The final stage also includes the history of past outcomes. The competition environment is similar to the monopoly, except that in Stage 3 there are now two rating agencies, labeled randomly *Alpha* and *Sigma*. The sellers are able to observe the fees and the reports from both agencies, but then must decide which report, if any, to accept.

The instructions read to the participants at the beginning of each session are included in Appendix A. We also provide screenshots of the user-interface in Appendix B. Subjects were paid for six random periods in the session at the rate of $1 per 38 points. We also paid an additional minimum show-up fee of $5, and increased uniformily in each session and according to role to improve subject earnings. On average, sessions lasted just under 50 minutes. Average earnings per player type are summarized in Table 1.

4 Results

We begin our analysis with a brief overview of the summary statistics presented in Table 2. Our analysis is based on a restricted data sample of the last 16 periods of every session. We do this to eliminate the learning period that generally occurs in early rounds.

The top section of Table 2 displays the summary statistics for the CRA. We see that inflation is much more prevalent in the monopoly treatment (MT). In fact, the mean inflation in a MT is 27, which is almost twice as high as the mean of 15 under competition (CT). Inflation, defined as issuing a blue report when the signal is red, also has a higher variance under a monopolistic market structure. The fee for the report is higher in the MT than in the CT, 51 and 27 respectively, which is in line with our expectations that prices are lower in competitive settings.

Table 2: Summary statistics (periods 9-24)

	Monopoly		Competition	
	Mean	SD	Mean	SD
Rating Agency (CRA)				
Fee	51	13	27	15
Inflation (%)	27	23	15	16
Seller, acceptance rate (%)				
At least one	42	18	75	10
Blue	54	24	81	8
Red	13	12	35	15
Blue (mixed)	–	–	59	28
Red (mixed)	–	–	9	13
Buyer, bids				
Blue	80	19	75	11
Red	23	9	20	8
No report	39	10	24	9

"Mixed" refers to the scenario in which CRAs offer conflicting reports (blue and red).

The middle section of Table 2 looks at the seller acceptance rate of the CRA reports. We present summary statistics for acceptance rate of at least one report and then classify the acceptance rate according to report type. Therefore, we present acceptance rates of at least one report that is blue, at least one report that is red, and lastly, in the case of competition, when the reports are conflicting (blue and red). Note that in the first category for the MT there is only one report in the market. The results suggest that acceptance is higher under CT regardless of report classification. For example, 35 percent of red reports are accepted in CT, compared with 13 percent in MT. This result may driven by lower fees in the competitive environment. Acceptance rate for blue reports is 81 percent in the CT versus 54 percent in the MT. In the case of mixed reports, sellers accept blue reports more than half of the time (59 percent) and red reports less than 10 percent of the time.

Given that we use an exceptionally accurate signal, $e = 0.9$, the acceptance of blue reports when the CRAs issue conflicting reports, suggests that sellers are a complicit in inflation and are indirectly signaling the CRAs to inflate. This is supported by the fact that in approximately 23 out of the 64 periods in which sellers encounter mixed reports, CRAs purposely inflate ratings. Despite this, inflation is still lower in the CR, which is the only treatment where mixed reports can occur.

The lower section of Table 2 provides on overview of buyer behavior. Buyers behave more rationally in the CT compared to MT when no report is issued, where on average the bids for the asset are much lower (24 vs. 39). However, bids in the MT may be higher because fewer reports are published, and therefore the buyers are uncertain about the widget type and report accuracy, or lack thereof. Futhermore, bids when red reports are issued are relatively accurate in both treatments (23 in MT and 20 in CT), while bids for the asset when blue reports are issued are lower (80 in MT and 75 in CT) than the actual (120) or expected (110) asset value under the specified signal precision.

Next, we introduce regression analysis to evaluate player behavior in each role. In particular, we are most concerned with variables that affect inflation and fees. Table 3 presents results for three different specifications, using random effects and clustering observations for each independent pit. In specification (I) of Table 3, we estimate a logit regression for inflation when the CRAs observe a red signal. We incorporate the treatment effect, measured with the variable *Monopoly*, that takes the value of one when the treatment is monopoly and zero otherwise. We find that in the MT the odds of misreporting are 3.69 ($= \exp(1.31)$) higher than the CT. This coefficient is significant at 10 percent level ($p < .10$), which is not surprising given the high variance of inflation in the MT.

The other two specifications in Table 3 analyze the fees posted by the CRAs. The treatment effect is quite strong ($p < 0.01$) and suggests that less competition (monopoly) leads to an increase in the posted fee by about 24 points. In specification (III), we analyze whether the CRAs that inflate also set higher fees. The results indicate that inflation leads to an increase in the posted fee by about 11 points ($p < 0.05$). This increment is similar to the exogenous cost of misreporting (10 units).

Next, we analyze the seller decision via four different specifications in Table 4. The first two specifications combine data available from both treatments within the restricted 16 period time frame, while specifications (III) and (IV) focus on each treatment separately. All specifications include subject random effects and clustered standard errors at pit level. In specification (I) we look at the rejection of reports as a censoring problem. Therefore, we estimate this specification using a Tobit, in which the dependent variable is the accepted

Table 3: Rating agency decision

	(I) Inflate	(II) Fee	(III) Fee
Constant	-3.05^{***}	27.14^{***}	26.28^{***}
	(0.04)	(3.84)	(3.61)
Monopoly	1.31^{*}	24.25^{***}	23.54^{***}
	(0.79)	(5.41)	(4.95)
Inflate	–	–	10.75^{**}
			(5.13)
Inflate $\times$ Monopoly	–	–	0.42
			(8.22)
R^2	–	0.13	0.14
N	380	768	768

All models are estimated using subject random effects and clustered standard errors at pit level (using bootstrap). (I) is a logit model and constrains the sample to red signals only.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$

fee. The results show that the blue report is accepted with a fee of about 10 points in the CT. The accepted fee increases by about 20 points in the monopoly setting. We omit the interaction between the treatment effect and the blue report because it is not significant.

In specification (II) of Table 4 we analyze the acceptance decision using a logit model. We look at the probability of accepting at least one report and find that in the CT, the odds of accepting a report are 5.13 ($= 1/exp(-1.63)$) times higher than in the MT. This result is in line with the higher fees observed in the MT. High fees cause sellers to reject regardless of report type.

We also estimate the impact of report type and fee on the acceptance rate by treatment, with specifications (III) and (IV) of Table 4 presenting results for the MT and CT respetively. Our findings suggest that blue reports are accepted at a higher rate relative to red reports in both treatments (2.50 and 1.25, in log odds, respectively). The lower estimated coefficient in the CT captures the fact that only one report of the two issued can be accepted. That is, a seller in the competitive environment may observe two blue reports, but can only accept one, thus affecting the likelihood of acceptance over all blue reports. In the case of fees, a 10 point decrease (slightly smaller that the standard deviation for both treatments in Table 1), increases the probability of acceptance of a report by 0.3 (0.6), log odds, in the MT (CT). This indicates that fees are relatively more important in the CT. We also check whether the blue report is preferred when the seller is presented with two mixed reports. The probability of accepting a blue report in this case increases by 1.84 (log odds).

Lastly, Table 5 presents our analysis of the buyer decision. In the first two specifications, we estimate the impact of report type and market format on a buyer's bid. The first specification shows that when buyers do not observe a report in the competition treatment, they bid about 25 points for the widget. In the case of blue report, the bid increases by

Table 4: Seller decision

	(I) Fee [all]	(II) Accept [all]	(III) Accept [monopoly]	(IV) Accept [competition]
Constant	-7.92^{**}	1.27^{***}	-0.70	0.17
	(3.89)	(0.23)	(0.60)	(0.27)
Monopoly	19.97^{***}	-1.64^{***}	–	–
	(4.36)	(0.05)		
Blue	17.13^{***}	–	2.50^{**}	1.25^{***}
	(3.35)		(1.16)	(0.24)
Mixed	–	–	–	-1.09^{**}
				(0.47)
Blue $\times$ Mixed	–	–	–	1.84^{***}
				(0.58)
Fee	–	–	-0.03^{**}	-0.06^{***}
			(0.01)	(0.02)
Wald χ^2	36.56	24.93	6.19	35.13
Prob. $> \chi^2$	0.00	0.00	0.04	0.00
N	768	512	256	512

All specifications are estimated using subject random effects and clustered standard errors at the pit level (using bootstrap). All specifications are estimated using a logit model, except (I) which is a Tobit model. Censoring occurs when the report is rejected at the fee posted.

$^{***} p < .01$, $^{**} p < .05$, $^{*} p < .1$

approximately 49 points, and in the case of red report, the bid decreases by 4 points, but it is not significant. This means that buyers value having no report the same as observing a red report or that the buyers are relatively sophisticated.

In the MT, the bids are higher by about 18 points when no report is published relative to the CT. This is consistent with having less reports published due to rejection by sellers and thus increasing uncertainty regarding the true widget value. Note that the interaction treatment dummy with red report has a negative coefficient that cancels out the added value of no report in the MT. This tells us that buyers bid lower in the monopoly treatment when a red report is issued compared to the case when no report is issued by approximately 18 points. Therefore, in the monopoly treatment the buyers do not view a lack of a report similar to a red report, as was the case in the CT.

In order to compare the gap between the winning and losing bid, we add a dummy variable in column (II) of Table 5. On average, the winner bids 23 points higher than his peer. The specification omits all interaction terms using the winner variable since they are not significant.

In the final two specifications, we attempt to determine which market format is more efficient. In our environment, the loss of efficiency is due to the penalty incurred by the CRAs when they misreport the signal. The total number of periods in which penalties are levied in the MT and the CT are 16 and 17, respectively. We believe that the reason for the low number of penalities in the MT is due to rejection of reports because of high fees.

Table 5: Buyer decision

	(I) Bid	(II) Bid	(III) Surplus	(IV) Surplus
Constant	25.23^{***}	13.55^{***}	-25.25^{***}	6.36^{***}
	(2.73)	(2.54)	(4.52)	(3.73)
Blue	48.81^{***}	49.33^{***}	65.59^{***}	–
	(3.60)	(3.54)	(6.03)	
Red	-4.19	-4.05	–	–
	(3.04)	(3.01)		
Monopoly	17.47^{***}	17.76^{***}	-14.47^{***}	-3.20
	(3.34)	(3.34)	(5.54)	(5.46)
Blue × Monopoly	-9.16	-9.70	20.47^{**}	–
	(8.41)	(8.42)	(9.74)	
Red × Monopoly	-18.75^{***}	-18.39^{***}	–	–
	(5.92)	(5.53)		
Winner	–	22.75^{***}		
		(1.62)		
R^2	0.48	0.61	0.59	0.00
N	1024	1024	512	512

The linear model $Y = BX$, where X includes intercept and dummies, is estimated using subject random effects and clustered standard errors at pit level (using bootstrap).
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$

Recall that if the seller rejects the report, whether or not the CRA inflated ratings becomes irrelevant. In the MT, the buyers often do not observe any reports and therefore there is no penalty imposed on the CRAs.

An alternative variable of interest that can help measure efficiency is buyer welfare. Columns (III) and (IV) in Table 5 summarize the surplus of buyers who purchase the widget. Note that when analyzing buyer surplus, blue refers to the state rather than the report, as in columns (I and II) of Table 5. We observe that in the red state, a buyer in the MT receives about 15 points less compared to a buyer in the CT. When the state is blue, a buyer in the MT receives 21 points more. If we omit the dummies for asset type (specification IV), and only analyze the treatment effect, then we find that the surplus in the MT is 3 points lower, though this difference is not statistically significant.

The negative sign of the treatment effect indicates that a lack of report in the MT relative to the CT hurts the buyers in the red state, but benefits them in the blue state (positive coefficient on the interaction variable in specification III). We would like to highlight that competition among buyers lower surplus, specially when the information regarding widget type is reliable. If buyers believe that a report is accurate, then their bids approach the underlying widget value, which decreases their surplus to zero.

Below, we summarize our main results:

Result 1 *In the CT, bids from buyers when no report is posted are similar to bids when a red report is posted, indicating that buyers may be sophisticated. We do not find evidence* *of this in the MT.*

Result 2 *The fee when the rating agency inflates is higher than when it does not inflate. However, we also observe that the fee when the rating agency reports truthfully can be above $e\rho$, in particular in the MT.*

Result 3 *Inflation is more likely to occur in the MT.*

Result 4 *The (accepted) fee in the CT is about 20 points lower compared to the MT.*

Result 5 *When the state is red, buyers in the CT are better off compared to the buyers in the MT. When the state is blue, buyers in the MT are better off.*

5 Discussion

Using an experimental approach, we show how competition can increase truth-telling in a game in which intermediaries (CRAs) have access to reliable information regarding asset type traded in a market. The environment is motivated by the theoretical work of Bolton, Freixas and Shapiro (2012), who rely on exogenous cost to address reputational concerns that arise when issuing fraudulent reports.

Whether competition in the ratings market leads to a more optimal outcome depends on a number of factors. For example, when the ratings market becomes more competitive, there is a possibility of ratings shopping. That is, if the seller is not pleased with the report offered by a particular CRA, he can continue to search for a better report. This is not efficient not only due to loss of information, since reports that are not purchased remain unpublished, but also because this creates an incentive for the CRAs to inflate ratings. On the other hand, increased competition amongst CRAs can drive down report fees, making inflation costly. In conjunction with higher proportion of sophisticated buyers (recall that inflation equilibrium required a high proportion of naive buyers), this provides the correct incentives for truth-telling, as CRAs become more concerned about reputation.

Our results indicate that competition does drive down fees to levels lower than or equal to the cost of reputation. This indeed makes ratings inflation costly and therefore realigns the incentives of the CRA to be more truth-telling. Therefore, the effect of competition on the morals of markets does not appear to be deleterious in economic experiments. Aside from the evidence provided here, Bartling, Weber and Yao (2015) also determine that unfair products, which result in a negative externality for third parties, are not transacted in markets despite significant economic incentive to flood the market with such goods.

There are a number of ways to extend this work and improve our understanding of the ratings market dynamics. One possibility is to introduce endogenous costs (e.g. see Mathis, McAndrews and Rochet, 2009), and then include communication between sellers and CRAs. Such experiment could provide more information on whether our initial approach is correct and whether the competition effect holds when the experimental design is modified. Furthermore, there may be a threshold number (as suggested by Hirth, 2014) of CRAs that minimizes the conflicts of interest. We only provide evidence in support of competition, but do not quantify the optimal level of competition.

Lastly, from what we know of existing literature, there is no clear guide to behavior of market participants during business cycles, which can be interpreted as a good or bad asset states in our game. For example, there is some evidence that in a downturn, people are more likely to default when the volatility is high (e.g. see Rabanal, 2013). Similarly, there is experimental evidence that inflation increases (truth-telling declines) during economic downturns (e.g. see Kluger and Slezak, 2015). However, collectively, there is still much to be studied in this area. We believe that additional research can provide deeper insights regarding behavior and motivation of agents during business cycles as well as the role of rating agencies in the resulting outcomes.

6 Acknowledgments

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Appendix A: Instructions (competition treatment)

Welcome! You are participating in an economics experiment at CEED Lab. In this experiment you will participate in a market game. If you read these instructions carefully and make appropriate decisions, you may earn a considerable amount of money that will be immediately paid out to you in cash at the end of the experiment.

Each participant is paid $5 for attending. Throughout this experiment you will also earn points based on the decisions you make. The rate at which we exchange your points into cash will be explained to you shortly. We reserve the right to improve this in your favour if average payoffs are lower than expected.

Please turn off all cell phones and other communication devices. During the experiment you are not allowed to communicate with other participants. If you have any questions, the experimenter will be glad to answer them privately. If you do not comply with these instructions, you will be excluded from the experiment and deprived of all payments aside from the minimum payment of $5 for attending.

The experiment you will participate in will involve interaction in a market setting. In this market, there are buyers, sellers and intermediaries. Once you begin playing, you will be assigned a specific role that you will keep throughout the duration of the experiment.

In the market, sellers will be selling a good called "widgets" to buyers. These widgets have an uncertain color. Blue widgets are highly valuable to buyers while red widgets are worth considerably less. Intermediaries are tasked with evaluating the color of the widgets. You will be playing a series of rounds. Each round will consist of decisions made by intermediaries, sellers and buyers. In the instructions below we explain how your decisions as a buyer/seller/intermediary will affect your points and total earnings.

The experiment

The experiment will feature a number of rounds. In each round, you will be assigned to a market that consists of 1 seller, 2 intermediaries and 2 buyers. While the markets you interact in will change throughout the course of the experiment, your role will remain the same.

Each round, a seller will have a single widget to sell. Neither the seller nor the buyers know the color for certain before making a transaction. They do, however, know that the widget is blue with the probability of 50% and red with the probability of 50%. The intermediaries each have access to research teams that can observe the correct color with a 90% probability. The seller observes both intermediaries requested fees and their reported colours for the widget, and can hire up to one intermediary to issue their report to buyers about the color of the widget.

Each round will consist of five stages.

Stage 1 (10 seconds): Each **intermediary** will privately decide how much to charge for his or her report. This amount can be any number between 0 and 120.

Stage 2 (10 seconds): Each **intermediary** will then receive costless information from its research team on the color of the seller's widget. This information is accurate 90% of the time. Each intermediary receives an independent draw of information from their research team (thus it is possible that two intermediaries assessing the same good receive different information). Each intermediary must then decide what color to report to the seller (blue or red).

Stage 3 (10 seconds): The **seller** receives the reports and fees of both intermediaries. Notice that the fee asked by the intermediary is set prior to receiving any information from the research team. The seller must then decide either to (i) accept only one of the two fees and publish the report of the selected intermediary for buyers to view or (ii) reject both reports and fees. If the seller rejects both reports, buyers will be notified "No report is available".

Stage 4 (10 seconds): The **buyers** observe either (i) a blue report, (ii) a red report, or (iii) "No report is available". The buyer will also be informed about the fee associated with the report (if any). They must then decide individually how much to bid on the widget. The buyer that submits the highest bid will pay her bid and receive the widget. **The winning buyer receives 120 points if the widget is blue and 20 points if it is red.** The other buyer will not pay anything and will not receive any points. If both buyers submit the same bid, the computer will randomly decide with 50-50 probability which buyer to award the widget to.

Stage 5 (10 seconds): **All players** observe the outcome of the round. They will learn what the winning bid was, the actual color of the widget and their own earnings.

In each round, all **intermediaries** are endowed with 10 points. The endowment can be taken away from the hired intermediary if they report the widget is blue when s/he was informed it was red by their research team AND the widget is revealed to be red.

EARNINGS

Your earnings will be computed according to the formula for your role:

Sellers:

Earnings of a Seller = Winning Bid - Fee Paid to Hired Intermediary (if they hired one)

Buyers:
Earnings of a Winning Buyer = Value of the Widget - Winning Bid
where the Value of the Widget is 120 if the widget is blue and 20 if the widget is red.

Earnings of the Other Buyer = 0

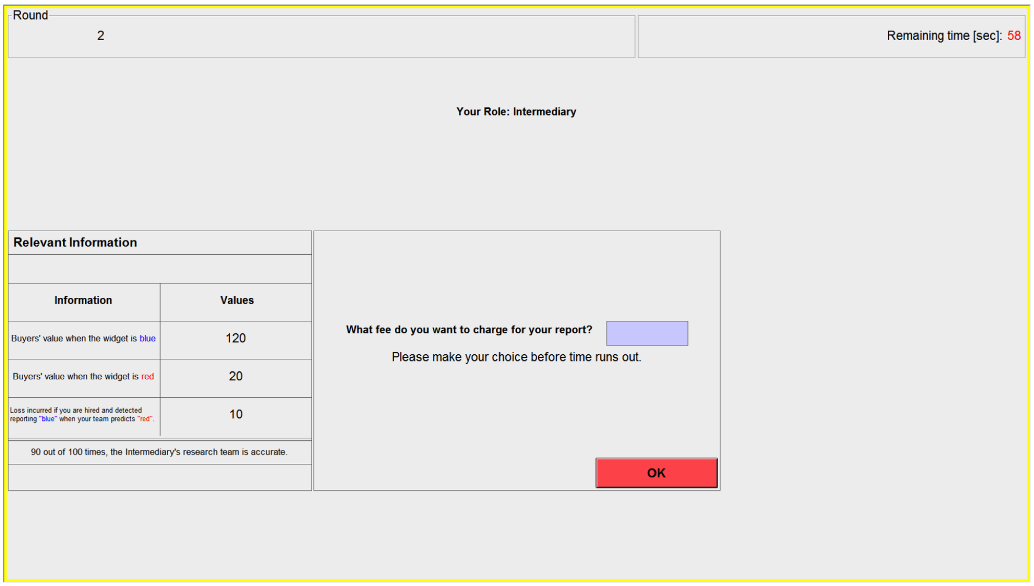
Intermediary:
Earnings of a Hired Intermediary = Report Fee + Endowment
The endowment will be 0 if the hired intermediary is found to report blue when his or her research team informed them the widget was likely red AND the widget is actually red, and 10 otherwise.
Earnings of the Other Intermediary = Endowment

There are 20 participants in this session. There will be four markets at any point. Every round you will be rematched with 4 strangers from your group only. While you will not know who you are playing with, you will end up interacting with players more than once. No two markets you participate in will have exactly the same people.

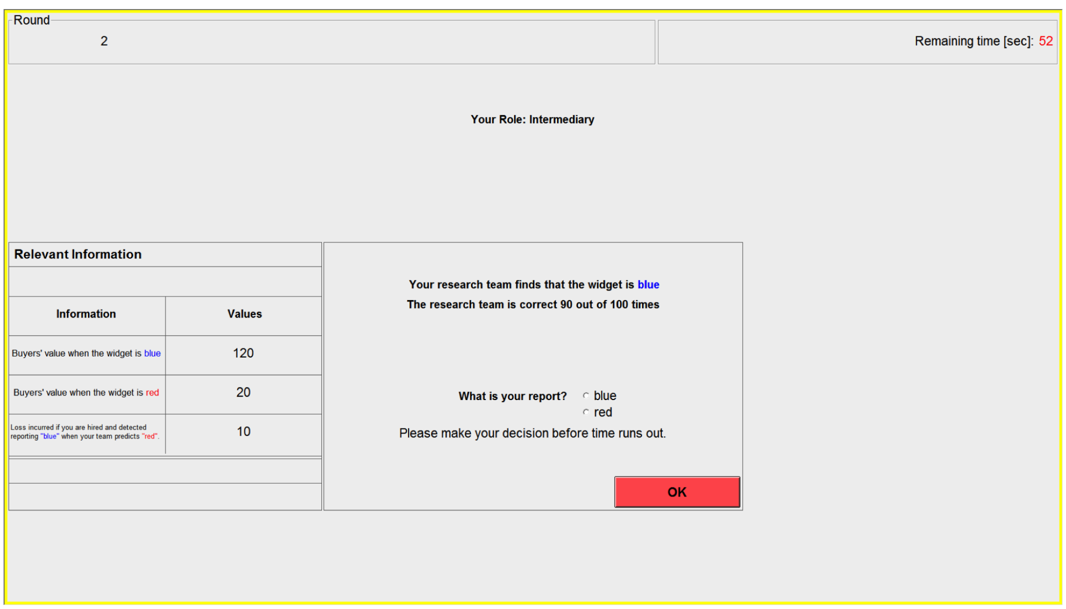
The points you earn from 6 randomly selected rounds will be added up, exchanged into dollars and paid to you, along with your show up fee, in cash at the end of the experiment. Your exchange rate is written on the board.

Can I earn negative points? Yes, all players can potentially earn negative points based on their decisions and the decisions of others. If, at the end of the experiments, your total points are negative, we will deduct your show up fee the required amount up to $5.

Appendix B: User interface (monopoly treatment)

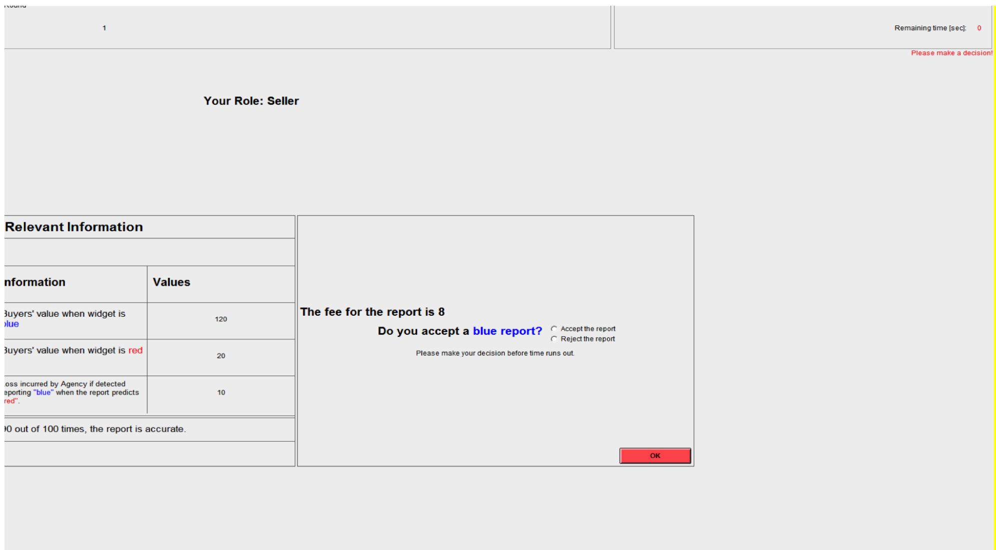


(a)

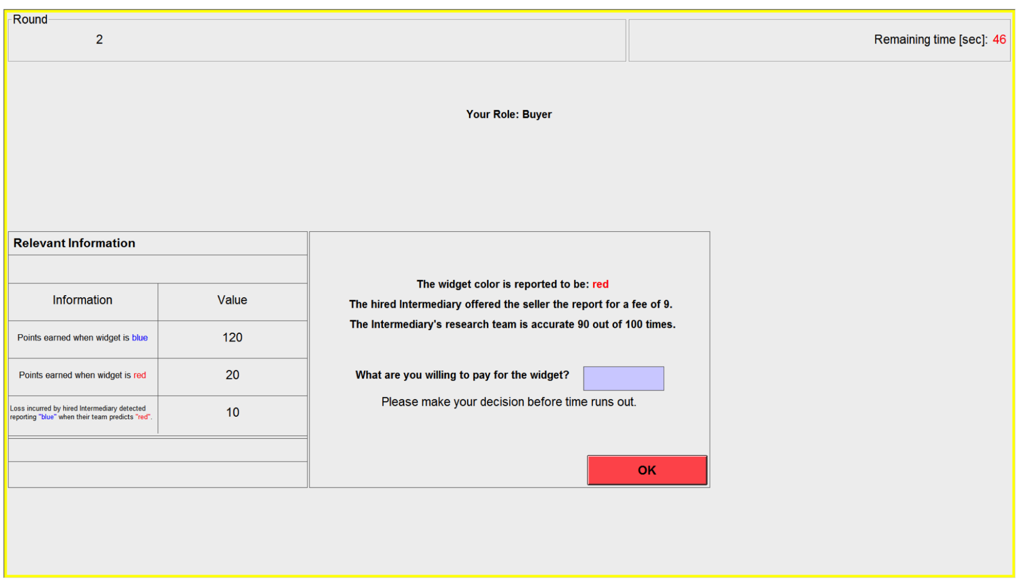


(b)

Figure 1: Intermediary's interface



(a)



(b)

Figure 2: (a) Sellers and (b) Buyers interfaces

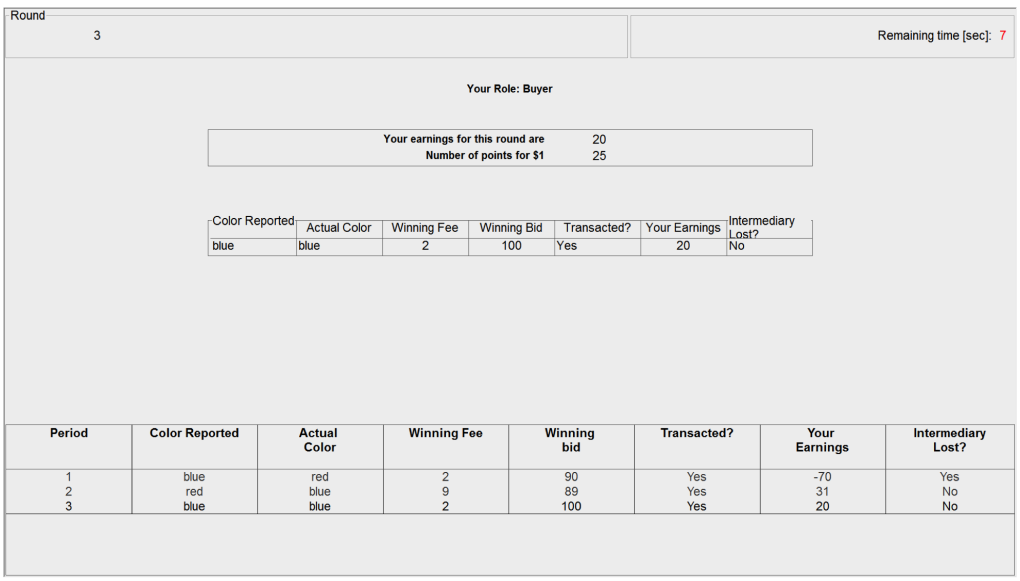


Figure 3: Results interface