Three Essays on How Product or Social Information Increases Efficiency

by

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To my family, friends and colleagues

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Abstract

This dissertation includes three essays on how product or social information increases efficiency. Chapter 1 is an overview. Chapter 2 and Chapter 3 investigate how information about product or service quality affects market efficiency. Chapter 4 discusses how information about an individual's social position influences her tendency to maximize the welfare of her social group. Chapter 5 concludes.

Chapter 2 examines the inefficiency problem in credence goods markets caused by sellers' provision of service with unnecessarily high costs and buyers' excessive requests for compensation after service failure. I investigate whether this market inefficiency can be alleviated through a reputation system and/or a behavioral nudge. I show that when there is a reputation system which makes sellers' action history and buyers' reactions publicly visible, there exists a perfect public equilibrium in which the seller and buyer frequently play the Pareto-efficient strategy profile. I also predict that a behavioral nudge, which makes salient the Pareto-efficient outcome, encourages them to play the Pareto-efficient strategy profile. My laboratory experiment results show that buyers are significantly less likely to request compensation when the reputation system is introduced. When both the reputation system and the nudge are present, sellers are significantly less likely to provide service with excessively high costs in the late stage of the game, and market efficiency is weakly improved.

Chapter 3 focuses on markets where reliable information about product qualities is not available to buyers. In such markets, only a product quality testing organization has expertise in finding out and revealing true qualities of products to buyers. However, the testing organization

often has a limited testing capacity, and many existing testing mechanisms are unable to provide quality information of products that are most preferred by buyers. We design a product testing mechanism which not only makes full use of the limited testing capacity to only provide quality information of the best and cheapest products in the market, but also incentivizes enough sellers to produce products with high qualities and at a price equal to the marginal cost. Our experimental results show that the consumer surplus is significantly improved when the testing organization uses our proposed mechanism.

In Chapter 4, we test whether "we-thinking", group-regarding behavior in the presence of an individual-group tradeoff, is predicted by a specific relationship between group- and self-esteem. We define group- and self-esteem as having positive feelings about the relative performance of one's group and self. We proxy for group-esteem and self-esteem using rank-based measures and self-reported measures. We find that subjects' self-reported group-esteem (self-reported self-esteem) is significantly positively (negatively) correlated with engagement in "we-thinking". We also find that individual rank is significantly negatively correlated with engagement in "we-thinking" when group rank is high.

Chapter 1: Introduction

In economic and social interactions, information can change an individuals' utility function and thus influence market and allocational efficiency. In markets with information asymmetry, buyers' lack of information of whether sellers' products or services maximize their surplus may lead to sellers' inefficient production and pricing decisions and buyers' suboptimal purchasing decisions[1]. To solve this problem, economists find that institutional methods which forbid seller's inefficient provision of products (e.g., Dulleck et al., 2011) or asking third-party certifiers to provide accurate product information to buyers (e.g., Albano & Lizzeri, 2001) can effectively increase market efficiency. However, these methods may not be feasible due to some complicated features of the market or technical difficulties. The first stream of research in this dissertation investigate whether feasible informational and behavioral methods, which have been used in a wider range of contexts, can also lead to Pareto improvement in markets with information asymmetry. In social groups, the problem of inefficiency may also exist when group members are unwilling to make contributions to the group at the expense of their individual benefits. Previous literature has demonstrated that cognitive or situational methods such as priming the common social identity (e.g., McLeish & Oxoby, 2011; Chen et al., 2014) and establishing common experience among group members (e.g., Eckel & Grossman, 2005) can motivate group-regarding behavior. However, it is usually difficult to apply these methods in many real-life contexts and they may not have a long-lasting effect. In the second stream of my research, I investigate whether

[1] See Akerlof (1970) as an example.

we can use esteem, a social factor which is usually stable over time and prevalent in most realistic contexts, to predict an individual's willingness to make contributions to their social groups.

Chapter 2 investigates the market inefficiency problem in credence goods markets where the efficient treatment that maximizes consumers' expected utility does not solve the buyer's problem for sure. In credence goods markets, buyers "do not know what they need, but they observe the utility from what they get" (Dulleck et al., 2011, p.526). Only sellers, who provide the service, have the expertise to identify buyers' needs and then choose a treatment. In some credence goods markets, when the seller chooses a treatment that maximizes the buyer's expected utility (hereafter, sufficient treatment), there is a small but unavoidable probability of failure. In order to minimize the probability of failure, the seller must choose a treatment that incurs a higher cost to the buyers (hereafter, overtreatment), but the cost is so high that the utility from such an overtreatment is lower than the expected utility from a sufficient treatment. Whenever a failure happens, buyers are unsure whether the failure was caused by bad luck from a sufficient treatment or the seller choosing a treatment that is insufficient to solve the problem (hereafter, undertreatment). Buyers can choose to engage in "crying behavior", defined as behavior that expresses their dissatisfaction with the seller which increase their own (expected) utility at the expense of the seller's (expected) utility. To avoid the utility loss from buyers' crying behavior, sellers will overtreat ex-ante to minimize the chance of failure, and this behavior is called "defensive treatment". However, buyers' crying behavior and sellers' defensive treatments reduce both buyers' and sellers' (expected) utility, relative to the situation in which sellers provide a sufficient treatment and buyers do not engage in crying behavior.

In this chapter, I investigate whether the market inefficiency problem in credence goods markets with outcome uncertainty can be alleviated through a feasible reputation system and/or a behavioral nudge. I prove that with this reputation system established, there exists a perfect public equilibrium in which the Pareto-efficient strategy profile is played frequently, resulting in improved market efficiency. I also predict that a behavioral nudge which makes salient the information that sufficient treatment and not engaging in crying behavior leads to a Pareto-efficient outcome, can also improve market efficiency. My laboratory experiment results show that buyers are significantly less likely to "cry" when the reputation system is introduced. When both the reputation system and the nudge are present, sellers are significantly more likely to choose sufficient treatment and significantly less likely to overtreat in the late stage of the game, and market efficiency is weakly improved.

In Chapter 3, along with my co-author Ulrike Vollstaedt, I investigate markets in which consumers are only able to obtain credible information about a product's true quality through a third-party product quality testing organization. Albano and Lizzeri's (2001) theoretical framework demonstrates that a third-party certifier is able to increase market efficiency. Nevertheless, many real-life certifiers are only capable of testing a small fraction of products in the market. Typically, they select which products to test based on which ones are perceived to be of greatest interest for consumers. The limited testing capacity and relatively subjective criteria for which products should be tested usually do not guarantee that the quality information of products with the lowest price and best quality is revealed to consumers. These limitations will reduce consumer surplus.

We design a product testing mechanism, which we refer to as *SellersMayApply*, to make the best use of the certifier's limited testing capacity to maximize consumer surplus. We build a theoretical model for a product testing game. In this game, sellers make production, pricing and quality testing application decisions, and then a testing organization uses our proposed product testing mechanism to determine which seller(s)' products to test and report out about to buyers. Finally, buyers make purchasing decisions based on the qualities revealed by the testing organization and all sellers' prices. We prove that in all pure-strategy weak perfect Bayesian equilibria, all buyers purchase products that maximize their surplus. In addition to the *SellersMayApply* condition in which our proposed mechanism is applied, we also consider a *RandomTesting* condition in which the testing organization randomly tests the same number of products and reveals their qualities to buyers. The *RandomTesting* mechanism is a generic testing mechanism in which sellers cannot affect whether their products will be tested. Our laboratory experimental results show that the consumer surplus in the *SellersMayApply* condition is close to the maximum level and significantly higher than that in the *RandomTesting* condition.

Inefficiency also happens in social groups when members are unwilling to make contributions to their groups at the expense of their own benefits. In Chapter 4, I collaborate with Erin Krupka to investigate whether an individual's willingness to contribute to her group can be predicted by esteem, defined as an individual's positive feelings derived from her information about the relative position of her group (or her own). Although previous literature in experimental economists have found that priming (e.g., McLeish & Oxoby, 2011; Chen et al., 2014) or having common experiences (e.g., Eckel & Grossman, 2005) or interests (e.g., Guth et al. 2008) can motivate contributions to social groups, these methods or factors are usually difficult to effect in a natural setting or over the long term. R. Akerlof (2016) argues that group-esteem, the extent to which a person feels positive about her social identity, and self-esteem, idiosyncratic aspects of her identity (hereafter, individual identity), may be good predictors of when people are willing to make contributions to the group. As predictive factors, group-esteem and self-esteem are more stable and enduring compared with priming and common experience or interest.

To investigate the relationship between group-esteem (self-esteem) and willingness to make contributions to the group, we first adapt Akerlof's model (2016) by articulating how group-esteem and self-esteem affect an individual's willingness to contribute to her group's payoffs, and we predict that group-esteem (self-esteem) is positively (negatively) correlated with engagement in "we-thinking" behavior. To test these predictions, we conduct a laboratory experiment. In this experiment, we manipulate people's group-esteem and self-esteem by asking subjects to participate in inter-group and inter-personal competitions which vary the extent to which they feel positive about their social identity and individual identity. To experimentally proxy for group-esteem and self-esteem, we use rank-based measures and self-reported measures. Each subject's willingness to contribute to the group is measured by the number of tokens she allocates to maximize group payoffs at a cost to her individual payoff. We find that subjects' self-reported group-esteem (self-reported self-esteem) is significantly positively (negatively) correlated with engagement in “we-thinking”. Our results using the rank-based measure partially support the model’s predictions: Individual rank is significantly negatively correlated with engagement in “we-thinking” when group rank is high. The findings have implications for when individuals are likely to make contributions to the group at the expense of their personal payoff and for how to measure the psychological concept of group/self-esteem.

Taken together, my dissertation demonstrates the critical role that information plays in efficiency problems in markets and social groups. Chapters 2 and 3 show that efficiency in markets with information asymmetry can be improved through informational and behavioral methods, while Chapter 4 shows that people’s propensity to maximize efficiency in social groups can be predicted by their group- and self-esteem, which are based on information about their relative position.

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Chapter 2: Sellers' Defensive Behavior in Credence Goods Markets with Uncertain Outcomes: Does a Reputation System and/or a Behavioral Nudge Improve Efficiency?

2.1. Introduction

Information asymmetry exists in many markets and has been shown to cause market failure and inefficiency (e.g., Akerlof, 1970). A typical example of markets with information asymmetry is credence goods markets. In credence goods markets, buyers "do not know what they need, but they observe the utility from what they get." (Dulleck et al., 2011, p.526) Only sellers, who provide the service, have the expertise to identify buyers' needs and then choose a treatment.[2] As Dulleck et al. show (2011), sellers and buyers' asymmetric information about buyers' needs often result in Nash equilibria in which sellers choose treatments that reduce buyers' payoffs and/or buyers choose not to enter the market.

In some credence goods markets, a treatment that is widely considered appropriate may not guarantee a positive outcome. For example, in healthcare service markets, a medical treatment that is proven to be effective through clinical trials might still fail in some cases. In such markets, when the seller chooses a treatment that maximizes the buyer's expected utility (hereafter, sufficient treatment), there is a small but unavoidable probability of failure. In order to minimize the

[2] Examples include medical treatment, repair services of structurally complicated goods (such as cars and electronic devices), etc.

probability of failure, the seller must choose a treatment that incurs a higher cost to the buyers (hereafter, overtreatment), but the cost is so high that the utility from such an overtreatment is lower than the expected utility from a sufficient treatment.[3] Because of the uncertain outcome after a sufficient treatment and buyers' lack of information about their own needs, whenever a failure happens, buyers are unsure whether the failure was caused by bad luck from a sufficient treatment or the seller choosing a treatment that is insufficient to solve the problem (hereafter, undertreatment).[4]

Buyers' potential "crying behavior" against a failed treatment, and sellers' attempt to avoid the loss from such behaviors, lead to an inefficient market outcome. When a treatment fails, buyers sometimes choose to engage in "crying behavior", defined as behavior that expresses their dissatisfaction with the seller which increase their own (expected) utility at the expense of the seller's (expected) utility.[5] To avoid the utility loss from buyers' crying behavior, sellers will overtreat ex-ante to minimize the chance of failure. I refer to this type of overtreatment as "defensive treatment", a term adapted from "defensive medicine" in health economics.[6] However, buyers' crying behavior and sellers' defensive treatments reduce both buyers' and sellers' (expected) utility, relative to the situation in which sellers provide sufficient treatments and buyers do not engage in crying behavior.

This study tests whether defensive treatment and crying behavior happen in credence goods markets with uncertain treatment outcomes, and whether the problem of market inefficiency in

[3] An example is treating someone with the flu. A sufficient treatment is to ask the patient to rest at home and drink water, but there is still a small probability of fatal complications. An overtreatment would be hospitalization, which can detect the more rare but serious complications, and would reduce the probability of unlikely but severe consequences. For most patients, this is a case where the expected utility from a sufficient treatment is higher than from an overtreatment due to the high expenditure from hospitalization.

[4] Another consequence of uncertain outcomes from sufficient treatment is that it is technically more difficult to apply institutional restrictions to forbid undertreatment as that in Dulleck et al.'s paper (2011), because a treatment failure does not necessarily imply undertreatment.

[5] There are mainly two types of crying behavior. First, some buyers "cry" to force the seller to compensate them. Examples include filing a lawsuit against the seller, public protest, leaving publicly visible resentful comments, complaining with customer service repeatedly, etc. Fearing that the lawsuit or protest will harm their reputation in the long run (even if an official investigation is conducted and they are judged to be innocent), sellers might choose to compensate buyers privately to stop further crying behavior. Second, some other buyers "cry" for the purposes of venting their dissatisfaction with the seller. A typical example is when patients verbally, or sometimes physically, confront doctors after a failed medical treatment (see Section 2.2 for relevant literature). Patients obtain psychological utility because they feel that they have "punished" the doctor for his/her failure to treat their problems.

[6] See Section 2.2 for relevant literature about defensive medicine.

such markets can be alleviated through reputational or behavioral interventions.[7] Using a game theoretical model, I show that the unique perfect Bayesian equilibrium in the stage game is that sellers overtreat while buyers engage in crying behavior, when compensation from crying behavior is large enough. I then set up a reputation system in which each seller's individual history and buyers' aggregate history are publicly visible. I prove that with this reputation system established, there exists a perfect public equilibrium in which the Pareto-efficient strategy profile is played frequently, resulting in improved market efficiency. I also predict that a behavioral nudge which makes salient the information that sufficient treatment and not engaging in crying behavior leads to a Pareto-efficient outcome, can also improve market efficiency.

I use a laboratory experiment to test the model's predictions. The experiment has a 2x2 design. The different conditions vary whether the reputation system is present and/or whether the behavioral nudge is used. Sellers and buyers are randomly matched and play the game for more than 60 periods.

I find that when neither the reputation system nor nudge is present, sellers and buyers converge to the predicted Pareto-inefficient perfect Bayesian equilibrium in which sellers overtreat and buyers cry. In the condition with the reputation system alone, buyers are significantly less likely to engage in crying behavior as I predict. However, crying is far from being eliminated: the proportion of crying behavior is still higher than 70%. I also find that sellers are significantly less likely to choose the overtreatment strategy and significantly more likely to choose the sufficient treatment strategy in the late game when both the reputation system and nudge are present, although the likelihood of crying behavior is not significantly reduced. Examining sellers' and buyers' repeated game strategies across all conditions, I find that sellers' repeated game strategy tends to be closer to the model's predictions than buyers' repeated game strategy. Specifically, sellers tend to start with the sufficient treatment strategy and then switch to the overtreatment strategy as I predict. Most buyers start with crying behavior, and they will only significantly reduce

[7] An obvious solution to this inefficiency is that a third party conducts an ex-post investigation about the real cause of a failed treatment and only asks the seller to compensate the buyer when the seller undertreats, but such an investigation is oftentimes too costly or technically impossible to conduct.

their crying behavior when the reputation system is present and when their sellers choose the overtreatment strategy frequently. The post-experiment survey, which elicits sellers' and buyers' beliefs about the normative behavior[8] in the market, provides potential explanations for the high proportion of crying behavior in all conditions.

This paper contributes to the economics literature by analyzing the phenomenon of defensive treatment under the theoretical framework of credence goods markets and investigating sellers' and buyers' behaviors through a controlled laboratory experiment. Although there have been many empirical investigations about defensive treatment in health economics, this study is one of the few studies that illustrates the dilemma sellers and buyers face through a game theoretical model.[9] My controlled laboratory experiment is the first study that provides a clean environment to unravel the cause of defensive treatment. This is also the first study that introduces and formalizes the concept of "crying behavior" and integrates it into the discussion of defensive treatment and credence goods markets. To solve the dilemma and improve market efficiency, I propose a feasible reputation system in which sellers and buyers are theoretically able to reach a Pareto-improved equilibrium. This is one of the few studies that conduct a repeated game analysis to investigate the effectiveness of a reputation system in the literature of credence goods markets.[10] In addition to economic or informational methods that have been discussed in previous literature, this study also incorporates insights from behavioral economics. I find that a behavioral nudge, along with the reputation system, can discourage defensive treatment in the long run and weakly improve market efficiency. I also show that social "bias" against sellers might explain market inefficiency in these credence goods markets. This finding suggests that future investigations about efficiency problems in markets with information asymmetry might also need to consider social and/or psychological factors.

[8] In the context of this study, normative belief refers to what action sellers' and buyers' first- or second-order belief about the most socially appropriate action sellers or buyers should take.

[9] See Section 2.2 for a detailed review.

[10] See Section 2.3 for a detailed discussion of other relevant papers.

2.2. Literature Review

2.2.1. Features of Credence Goods Markets and Outcome Uncertainty

The concept of credence goods was first introduced by Darby and Karni (1973) to describe goods or service with the feature that buyers are not able to determine which type or version maximizes their utility, although they can observe their utility after consuming the good. Only the seller has the expertise to identify the quality level of service or goods that buyers need and then provide those to the buyers.[11] This information asymmetry between buyers and sellers leads to three broad classes of sub-optimal choices: overtreatment, undertreatment and overcharging.[12] All of these can lead to market inefficiencies (see Dulleck & Kerschbamer (2006) for a general discussion). Empirical studies confirm that these problems exist in many types of credence goods markets in real life, such as car repairs (Wolinsky, 1993, 1995; Hubbard, 1998) and medical treatments (Iizuka, 2007; Emons, 1997; Hughes & Yule, 1992).

Most theoretical models about credence goods markets assume outcome certainty. Outcome certainty means that the same treatment choice will lead to the same outcome (success or failure) with a 100% probability given the type of problem (e.g., Taylor, 1995; Pesendorfer & Wolinsky, 2003; Alger & Salanié, 2004; Dulleck & Kerschbamer, 2006; Dulleck et al. 2011). For example, Dulleck et al.'s model (2011) assumes that overtreatment and sufficient treatment can both solve the buyer's problem with a 100% probability, while undertreatment always fails to solve the problem. However, in reality this outcome certainty sometimes cannot be guaranteed.

There are models incorporating outcome uncertainty. In Bester and Ouyang (2018)'s model, a sufficient treatment and an overtreatment have the same success rate, so the difference in buyers' expected utility between these two treatments only comes from the difference in price but not the difference in expected value from a successful treatment. Batabyal and Batabyal's model (2018)

[11] In economics, there is a second definition of credence goods. According to this second definition, buyers can determine what quality they need but are unable to observe the true quality they purchase or the utility they receive. In the present paper, I use the first definition.

[12] When a seller overcharges, s/he charges a price for a high-cost treatment although s/he actually provides a low-cost treatment. It happens as a result of not only information asymmetry regarding the buyer's need but also information asymmetry regarding the seller's treatment choice.

consider two different treatment options with different success rates, but the treatment choice is made by the buyer rather than the seller, and there is no distinction between a sufficient treatment and an overtreatment. In Balafoutas et al.'s model (2020), the same treatment leads to a certain outcome, but the seller receives a noisy signal about the true type of the problem and the accuracy of this signal is positively correlated with the seller's effort on diagnosis. There is no essential difference in success rate between a sufficient treatment and an overtreatment. In some cases, however, overtreatment might slightly increase the success rate compared with a sufficient treatment.

2.2.2. Empirical Evidence of Crying Behavior and Defensive Treatment

Buyers' crying behavior after a failed treatment is a significant and prevalent problem but have received relatively little attention in the literature related to credence goods markets. A typical and extreme type of "crying" behaviors is verbal or physical confrontation in healthcare markets, defined as "incidents (in healthcare facilities) where staff are abused, threatened, or assaulted in circumstances related to their work, including commuting to and from work, involving an explicit or implicit challenge to their safety, well-being, or health." (World Health Organization, 2002) According to a 2011 US national survey, 78% of emergency room doctors reported that they have been victims of verbal or physical violence (Behnam et al., 2011). A national survey in China shows that more than 70% physicians have experienced verbal abuse or physical injuries in hospitals (Yang et al., 2019). Some empirical studies indicate that an important consequence of violence in the healthcare industry is that doctors are more likely to choose defensive treatments (Dudeja & Dhirar, 2018; He, 2014).

Empirical studies find that defensive treatments happen in many parts of the world. In health economics, doctors' overtreatment for purposes of avoiding patients' crying behavior is termed "positive defensive medicine".[13] There is ample empirical evidence showing that (positive)

[13] Defensive medicine is formally defined as medical treatment choices aimed at avoiding liability but with limited benefits for patients. There is also "negative defensive medicine", which refers to the phenomenon that doctors avoid treating patients who are likely to cause liability issues or avoid applying risky medical practices (Sekhar & Vyas, 2013).

defensive medicine is a world-wide problem in the healthcare industry. Many empirical studies demonstrate that positive defensive medicine happens in the United States (Reynolds et al., 1987; Willke et al., 1991; Kessler & McClellan, 1997; Agarwal et al., 2019; Keane et al., 2020), European countries (Toraldo et al., 2015; Garattini & Padula, 2020) and China (He, 2014).

Although much empirical literature has demonstrated the prevalence of buyers' crying behavior and sellers' defensive treatment, few studies have investigated the interaction between buyers and sellers and analyzed the dilemma they face through the framework of credence goods markets. Antoci et al.'s theoretical model (2016) is one of the few that investigates the interactions between sellers and buyers. In their model, sellers choose either defensive medicine or non-defensive medicine. It implicitly assumes that sellers who choose non-defensive medicine always provide a sufficient treatment and that buyers' litigation requests are never motivated by their lack of trust on sellers' treatment choice.

2.2.3. Using Reputation to Improve Efficiency

Since the most important feature that distinguishes credence goods from search goods is the information asymmetry between sellers and buyers, a natural idea to solve the market inefficiency problem is to use a reputation system that provides the behavior history of sellers and buyers to each other.

Some theoretical, empirical and experimental studies investigate the role a reputation system plays in repeated interactions among sellers and buyers. Darby and Karin (1973) argue that reputation building can help honest sellers avoid losses from price and quality competition with other sellers. Dulleck et al.'s experimental results (2011) demonstrate that the volume of trade increases and the proportion of overcharging decreases when each buyer can keep track of the identity of the matched seller.[14] In a recent study, Fong et al. (2022) investigate credence goods markets in which a seller's reputation is reflected by whether consumers reject the seller's

[14] Note that Dulleck et al. (2011) investigates a finitely repeated game with only 16 rounds, so sellers and buyers theoretically do not have the incentive to deviate from the Pareto-dominated Equilibrium. The present study considers an infinitely repeated game with a discount factor close to 1, so a Pareto-improved outcome is theoretically possible.

recommendation or not. They find that in the optimal equilibrium, the seller's profit does not achieve the first best, and there may exist undertreatment or overtreatment depending on the discount factor.[15]

2.2.4. Using Nudges to Promote Positive Behavior

Behavioral economists define nudges as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives." (Thaler & Sunstein, 2009) By influencing people's decision making through cognitive or psychological channels, nudges are oftentimes less costly than economic methods which directly alter people's economic incentives.

Nudges have been widely used to promote positive social behavior. Empirical evidence shows that informational nudges, such as providing information about other people's behavior or belief,[16] can be used to promote positive social behavior. For example, disclosing information about other people's or households' energy consumption can effectively encourage energy conservation behavior (Schultz et al., 2007; Nolan et al., 2008; Ayres et al., 2013). Other studies find that cognitive nudges, such as altering the default option and priming useful information, concepts or knowledge, can also encourage positive social behavior. Changing the default option can increase charitable donation (Goswami & Urminsky, 2016) and organ donation (Johnson & Goldstein, 2003; Abadie & Gay, 2006). Primers that trigger pro-social concepts such as morality and sharing (de Medeiros et al., 2021) or religious concepts (Shariff & Norenzayan, 2007) increase prosocial behavior.

In the next section, I introduce a game theoretical framework that describes the features of this type of credence goods markets and explains when and why defensive treatment and crying

[15] There are also studies which investigate how institutional restrictions affect market efficiency when reputation is available. Fong and Liu (2018) show that liability, which forbids sellers' treatment that will lead to a failure, may undermine a long-lived seller's incentive to provide the first-best treatment and thus cause inefficiency.

[16] In behavioral economics and social psychology, this is known as descriptive social norms.

behavior is the unique equilibrium. In addition, I show how a feasible reputation system or a behavioral nudge can theoretically improve market inefficiency.

2.3. Theoretical Framework

2.3.1. Settings of the Stage Game

Consider a credence goods market with one seller and one buyer.[17] Both are risk-neutral. A buyer encounters a problem, which is either a major one or a minor one, and only the seller can identify whether it is a major or minor problem. The problem is a major one with a probability of h and is a minor one with a probability of $(1-h)$. After identifying the buyer's problem type, the seller can choose either a high-cost treatment (q^h) or a low-cost treatment (q^l). If the buyer's problem is a major problem, then a q^h treatment is a sufficient treatment, while a q^l treatment would be an undertreatment. If the buyer's problem is a minor one, then a q^h treatment would be an overtreatment while a q^l treatment is a sufficient treatment.

When the seller chooses a sufficient treatment, the problem is successfully solved with a probability of λ ($\lambda > 0.5$) and fails to be solved with a probability of $(1-\lambda)$. When the seller chooses an overtreatment, the problem is successfully solved with a probability of 1. When the seller chooses an undertreatment, the problem is successfully solved with a probability of $(1-\lambda)$ and fails to be solved with a probability of λ.[18] The buyer cannot observe the problem type s/he has. However, the buyer observes both the treatment choice selected by the seller and whether the outcome was successful or not.

The seller charges the buyer an exogenously determined price p^h (p^l) and incurs an exogenously determined cost c^h (c^l) from a q^h (q^l) treatment. The buyer receives a value v from a successful treatment and 0 from a failed treatment. The buyer strictly prefers a sufficient

[17] The setting of this model is adapted from Dulleck et al. (2011).

[18] The small probability of success from an undertreatment describes another type of uncertain treatment outcomes that is opposite to a small probability of failure from a sufficient treatment. In healthcare service markets, it describes accidental success that occasionally happens for reasons such as the patient's unexpectedly strong immune system or other unusual physical conditions. To simplify the model, I assume that the probabilities of success and failure from undertreatment are symmetric to those probabilities from sufficient treatment.

treatment to an overtreatment and an undertreatment given the problem type, so one can infer the following relationship from this preference:

$$\begin{cases} \lambda(v-p^l)+(1-\lambda)(-p^l) > v-p^h \\ \lambda(v-p^h)+(1-\lambda)(-p^h) > (1-\lambda)(v-p^l)+\lambda(-p^l) \end{cases} \Leftrightarrow (1-\lambda)v < p^h - p^l < (2\lambda-1)v \quad (1)$$

If the seller chooses q^l and the treatment fails, the buyer is unable to determine whether the failure was caused by the seller's undertreatment or bad luck after a sufficient treatment. The buyer can then choose to "cry" with a "crying cost" $(\gamma < \beta)$ or stay calm without any cost. If the buyer chooses to cry, the seller will have to pay a compensation β to the buyer.[19] If the buyer chooses to stay calm, then nothing happens, and both the seller's and buyer's final earnings are equal to what they have already earned before the buyer's cry/calm decision.

If the seller chooses q^h and the treatment fails, the game ends. The buyer is not able to make a cry/calm decision in this situation, because q^h is never an undertreatment, so there is no uncertainty about the real cause of this failure. When a treatment succeeds, then the game ends as well. In this game, the seller has four strategies: $q^h q^h$ (overtreatment strategy), $q^h q^l$ (sufficient treatment strategy), and $q^l q^l$ (undertreatment strategy) and $q^l q^h$ [20] while the buyer has two strategies: *Cry* and *Calm*.

A feature in this market is that when *Cry* is not in the buyer's behavior set, then the seller strictly prefers a low-cost treatment to a high-cost treatment.

$$\Delta\pi \equiv (p^l - c^l) - (p^h - c^h) > 0 \quad (2)$$

This feature implies that sellers have an incentive to be irresponsible, careless or slack off. Buyers understand that this incentive is present and, after a q^l treatment, they concluded that a failed

[19] One can interpret this compensation payment β as an ex-ante expected compensation, as one can argue that there could be uncertainty regarding whether this compensation can be successfully made. To avoid making an excessively complicated model, I choose not to introduce another lottery for the compensation outcome, because this uncertainty is not the focus of this study.

[20] The first element represents the seller's treatment choice given that it is a major problem, while the second element represents the seller's treatment choice given that it is a minor problem. Thus, $q^h q^h$ means that the seller always chooses the high-cost treatment q^h even if it is a minor problem, so it corresponds to the overtreatment strategy; $q^h q^l$ means that the seller always chooses a sufficient treatment according to the problem type, so it corresponds to the sufficient treatment strategy. $q^l q^l$ means that the seller always chooses a low-cost treatment q^l even if it is a major problem, so it corresponds to the undertreatment strategy; $q^l q^h$ means that the seller undertreats when it is a major problem and overtreats when it is a minor problem.

treatment is more likely to have been caused by the seller's undertreatment rather than bad luck. For this reason, buyers choose *Cry* instead of *Calm*.

Figure 2.1 below shows the extensive form of this game.

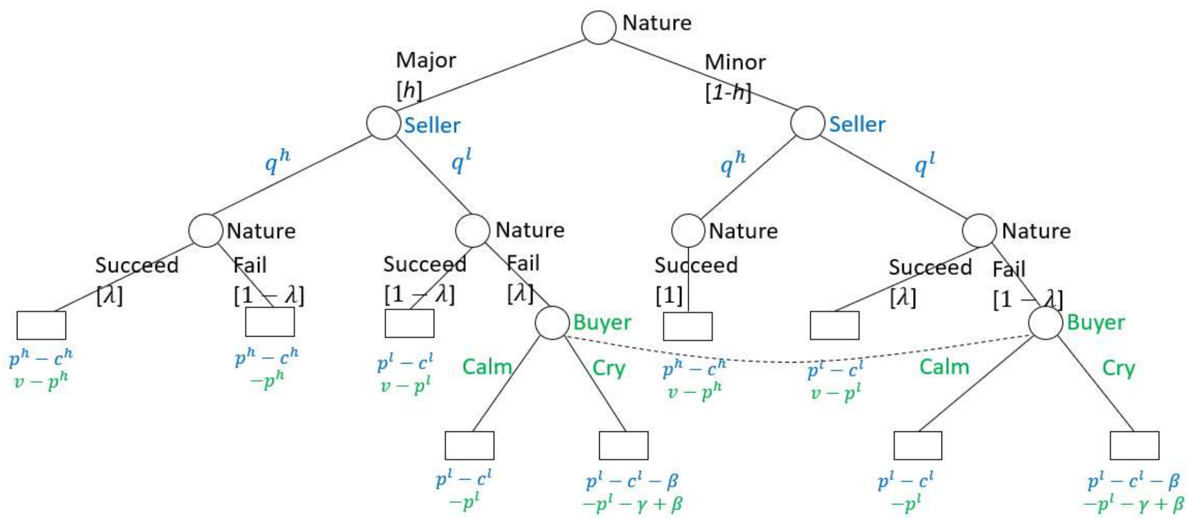

Figure 2.1. Extensive form of the game

2.3.2. Equilibria and Pareto Efficiency

It can be shown that when (1), (2) and (3) are satisfied, $(q^h q^h, Cry)$ (with the buyer's arbitrary belief in the information set) is the unique perfect Bayesian equilibrium, but it is Pareto-dominated by $(q^h q^l, Calm)$.[21]

$$\beta > \frac{\Delta\pi}{1-\lambda} \tag{3}$$

In other words, when (1), (2) and (3) are met, the seller will apply a defensive treatment of the problem and the buyer will cry. However, both the seller and buyer will be worse-off relative to a situation where the seller offers a sufficient treatment and the buyer does not cry.

[21] Note that the buyer's best response is always Cry regardless of her belief in the information set. When (1) to (3) are satisfied, the only best response for the seller will be $q^h q^h$.

2.3.3. The Repeated Game Without a Reputation System or Nudge

Consider a society with a finite number of sellers $\{s_i\}$ and buyers $\{b_i\}$. The stage game is infinitely repeated. In each period, a seller is randomly paired with a buyer, and the matching is reshuffled after each period. The interaction within each pair is anonymous so that each interaction is "without history" attached to the identity of either seller or buyer. However, at the end of each period, the seller's treatment choices (i.e., q^h or q^l), treatment outcomes (i.e., Success or Failure), the buyer's reaction (i.e., Cry or $Calm$, if available) in the period is only available to both the seller and buyer in the pair.

Due to anonymity and randomly reshuffled matching, it is difficult for a seller or buyer to establish reputation or punish the other for not being cooperative. In this sense, I predict that sellers and buyers are most likely to play the Pareto inefficient stage-game perfect Bayesian equilibrium in each period.

2.3.4. How a Reputation System Influences Behavior

Consider the game in Section 2.3.3 again. Different from the game in Section 2.3.3, I introduce a feasible reputation system: The seller's individual history in each of the previous periods, including her treatment choices (i.e., q^h or q^l), treatment outcomes (i.e., Success or Failure) and the buyer's reactions (i.e., Cry or $Calm$, if available), is visible to the buyer matched with this seller in the current period. Buyers' aggregate history, namely whether there exists *any* pair in which the buyer chooses Cry after a failure from the seller's q^l treatment choice, is visible to each seller and buyer. [22]

The game can be modelled as an imperfect public monitoring repeated game: Within each pair, the buyer can never observe the seller's complete strategy but can only observe the seller's treatment choice contingent on the problem type (which is exogenously decided by the nature) and

[22] Each seller's history is not visible to other sellers because I want to avoid mutual influence among different sellers. The reason that buyers' history is at the aggregate level is that it is usually unethical to track a buyer's individual history because of concerns such as invasion of privacy.

the treatment result. The buyer's behavior can be observed only when the seller chooses q^l and the treatment fails. The collection of these publicly visible behaviors or outcomes can be regarded as a public signal y. The set of public signals is $Y = \{HS, HF, LS, LFR, LFM\}$. HS (HF) corresponds to the seller choosing $q^{\boldsymbol{h}}$ and a **s**uccessful (**f**ailed) result. LS corresponds to the seller choosing $q^{\boldsymbol{l}}$ and a **s**uccessful result. LFR (LFM) corresponds to the seller choosing $q^{\boldsymbol{l}}$, a **f**ailed result and the buyer choosing *Cry* ($Cal\boldsymbol{m}$) Table 2.1 demonstrates the distribution of y given each strategy profile a.

Table 2.1. Distribution of public signals

Pr $(y\|a)$		y				
		HS	HF	LS	LFR	LFM
a	$q^h q^h, Cry$	$1-h(1-\lambda)$	$h(1-\lambda)$	0	0	0
	$q^h q^h, Calm$	$1-h(1-\lambda)$	$h(1-\lambda)$	0	0	0
	$q^h q^l, Cry$	$h\lambda$	$h(1-\lambda)$	$(1-h)\lambda$	$(1-h)(1-\lambda)$	0
	$q^h q^l, Calm$	$h\lambda$	$h(1-\lambda)$	$(1-h)\lambda$	0	$(1-h)(1-\lambda)$
	$q^l q^h, Cry$	$1-h$	0	$h(1-\lambda)$	$h\lambda$	0
	$q^l q^h, Calm$	$1-h$	0	$h(1-\lambda)$	0	$h\lambda$
	$q^l q^l, Cry$	0	0	$(1-h)\lambda$ $+(1-\lambda)h$	$1-(1-h)\lambda$ $-(1-\lambda)h$	0
	$q^l q^l, Calm$	0	0	$(1-h)\lambda$ $+(1-\lambda)h$	0	$1-(1-h)\lambda$ $-(1-\lambda)h$

Starting from Period 2, the seller's complete history of public signals in all previous periods is visible to the buyer matched with her in the current period, but it is not visible to any other seller or buyer. In addition, each seller and buyer will be notified of whether there exists any pair with a public signal of LFR. No further information is provided in terms of any other pair's public signal.

This notification will be anonymous so that no ID of the seller or the buyer is displayed.[23] Suppose that both sellers and buyers have a discount factor of δ.

Now I look for perfect public equilibria (PPEs) of this repeated game with the reputation system. It is obvious that the stage game perfect Bayesian equilibrium is a PPE of the repeated game. Formally, if I denote $\sigma_s(y^t)$ ($\sigma_b(y^t)$) as the seller's (buyer's) behavior given the history of public signals until Period t, then the strategy profile ($\sigma_s(y^t) = q^h q^h$, $\sigma_b(y^t) = Cry$; $\forall y^t$) is a PPE of the repeated game.

In addition, I find that there exists another PPE which Pareto-dominates the stage-game perfect Bayesian equilibrium. This PPE, which I call a "2-period punishment hybrid strategy profile", can be described by the following automaton: [24]

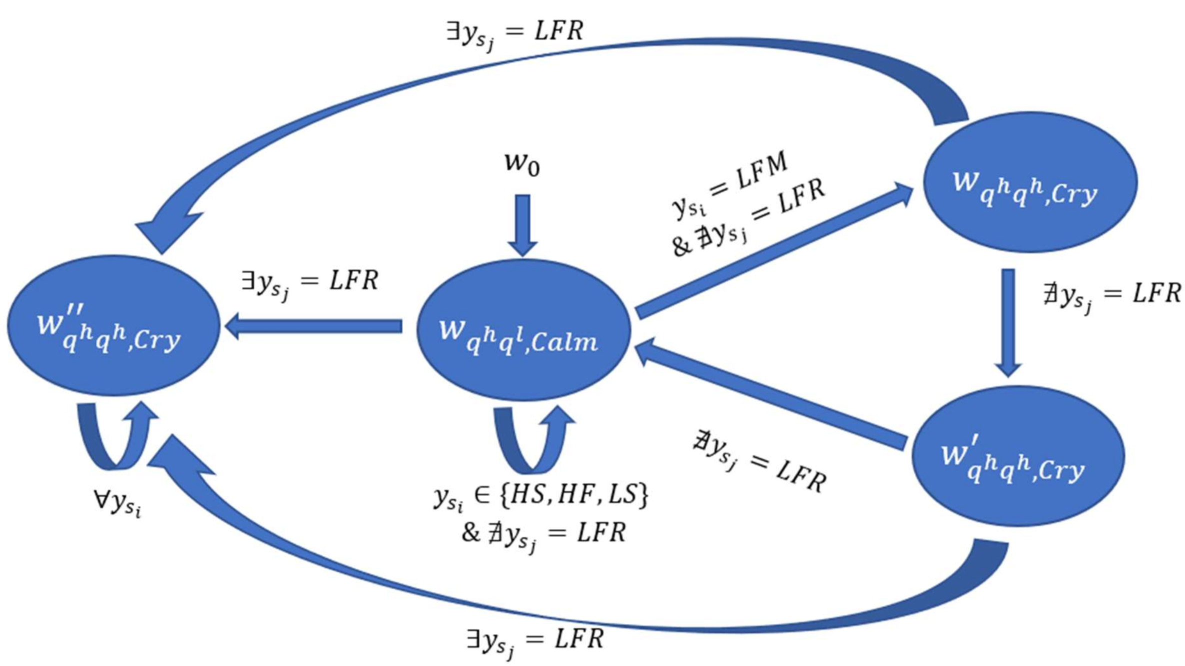

Figure 2.2. A 2-period punishment hybrid strategy profile

[23] This setting is to simulate many real-life situations in which each seller's history is publicly visible, while each buyer's reaction, although visible at an aggregate level, is not traceable at the individual level.

[24] This Pareto-improved PPE is found after I rule out some simpler strategy profiles. See Appendix 2.C for the intuition and procedures of ruling out other simpler strategy profiles and finding this PPE.

The state space is $W = \{w_{q^h q^l, Calm}, w_{q^h q^h, Cry}, w'_{q^h q^h, Cry}, w''_{q^h q^h, Cry}\}$. The initial state is $w_{q^h q^l, Calm}$. The output functions are $f(w_{q^h q^l, Calm}) = (q^h q^l, Calm)$, $f(w_{q^h q^h, Cry}) = (q^h q^h, Cry)$, $f\left(w'_{q^h q^h, Cry}\right) = (q^h q^h, Cry)$ and $f\left(w''_{q^h q^h, Cry}\right) = (q^h q^h, Cry)$. The transition function is:

$$\tau(w, y) = \begin{cases} w_{q^h q^l, Calm} & \begin{array}{c} \text{if } \left(w = w_{q^h q^l, Calm} \text{ and } y_{s_i} \in \{HS, HF, LS\} \text{ and } \nexists y_{s_j} = LFR\right) \\ \text{or } \left(w = w'_{q^h q^h, Cry} \text{ and } \nexists y_{s_j} = LFR\right) \end{array} \\ w_{q^h q^h, Cry} & \text{if } w = w_{q^h q^l, Calm} \text{ and } y_{s_i} = LFM \text{ and } \nexists y_{s_j} = LFR \\ w'_{q^h q^h, Cry} & \text{if } w = w_{q^h q^h, Cry} \text{ and } \nexists y_{s_j} = LFR \\ w''_{q^h q^h, Cry} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w''_{q^h q^h, Cry} \end{cases} \tag{4}$$

where y_{s_i} denotes the public signal from the seller s_i's pair, and y_{s_j} denotes the public signal from an arbitrary seller s_j's pair (including s_i's pair).

According to this automaton, each seller s_i will start with $q^h q^l$ while the buyer matched with s_i will start with $Calm$. If the public signal from s_i's pair in the previous period was HS, HF or LS and there did not exist any pair with a public signal of LFR,[25] then s_i and the next buyer matched with s_i will continue playing $(q^h q^l, Calm)$ in the next period. If the public signal from s_i's pair in the previous period was LFM and there did not exist any pair with a public signal of LFR, then in the next two periods, s_i and the next two buyers matched with s_i (or the next one buyer if the same buyer happens to be matched with s_i in both two periods) will play $(q^h q^h, Cry)$. After these two periods, s_i and the next buyer matched with s_i will return to playing $(q^h q^l, Calm)$. If there exists any pair with a public signal LFR in any period, then all sellers and buyers will perpetually switch to playing $(q^h q^h, Cry)$ in all the following periods.

I prove that the strategy profile described by the abovementioned automaton is a PPE if the following conditions are met.

[25] Recall that each pair is informed of whether there exists any pair with a public signal of LFR in the previous period.

Proposition 1. *The 2-period punishment hybrid strategy profile described by the automaton in Figure 2.4 is a PPE, if (1) to (3) are satisfied, δ is sufficiently large and the following additional conditions are met:*

$$\begin{cases} \delta(1+\delta)(1-h)(2\lambda-1)-1 \geq 0 & (5) \\ \delta(1+\delta)(1-h)h(2\lambda-1)+(1-2h) \geq 0 & (6) \end{cases}$$

Proof: See Appendix 2.A.

Figure 2.3 demonstrates the ranges of h and λ that satisfy (5) and (6) when δ takes different values.

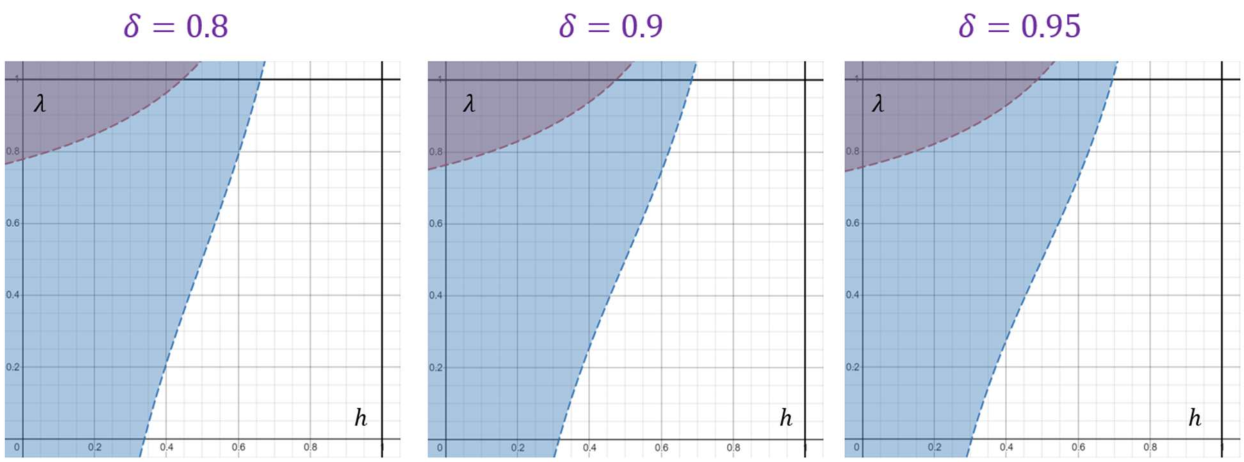

Figure 2.3. Ranges of h and λ that makes the 2-period punishment hybrid strategy profile a PPE

Note: The red area indicates the ranges of h and λ that satisfy (5); The blue are indicates the ranges of h and λ that satisfy (6).

If all sellers and buyers play this strategy profile and do not deviate, then each seller will transit among the three states $w_{q^h q^l, Calm}$, $w_{q^h q^h, Cry}$ and $w'_{q^h q^h, Cry}$, and the probability of being in these three states follows this Markov chain:

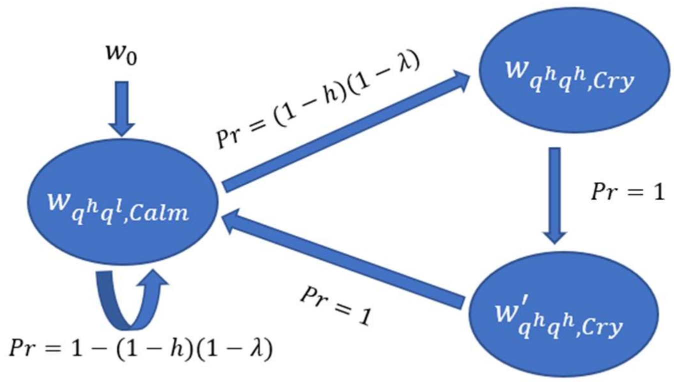

Figure 2.4. Transition of states if all players play the 2-period punishment hybrid strategy profile

Denote each seller's probability of being in the Pareto-efficient state $w_{q^hq^l,Calm}$ in Period t $(t = 0,\ 1,\ \dots)$ as ψ_t. Since each buyer is randomly rematched with a seller in each period, ψ_t is also each buyer's probability of being in the Pareto-efficient state $w_{q^hq^l,Calm}$ in Period t. I can prove that as $t \to \infty$, ψ_t converges to a constant.

Proposition 2. *If all sellers and buyers follow the 2-period punishment hybrid strategy profile, then the probability that each seller and buyer is in the state $w_{q^hq^l,Calm}$ in Period t, ψ_t, converges to a constant as $t \to \infty$. Formally:*

$$\lim_{t\to\infty} \psi_t = 1 - \left(\frac{y-1}{r\cos\theta - 1} - \frac{C_2 r\sin\theta}{r\cos\theta - 1}\right)$$

where:

$$r = \sqrt{S_1^2 + S_2^2 - \frac{y}{3}(S_1 + S_2) - S_1S_2 + \frac{y^2}{9}}$$

$$S_1 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}},\ S_2 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}}$$

$$x = (1-h)(1-\lambda),\ y = 1-(1-h)(1-\lambda), \theta = \arctan\frac{\frac{\sqrt{3}}{2}(S_1 - S_2)}{\frac{y}{3} - \frac{1}{2}(S_1 + S_2)} + \pi$$

$$C_2 = \frac{a}{b},\ a = \frac{y^2-1}{r^2 \cos 2\theta} - \frac{y-1}{r \cos \theta - 1},\ b = \frac{r^2 \sin 2\theta}{r^2 \cos 2\theta} - \frac{r \sin}{r \cos \theta}$$

Proof: See Appendix 2.A.

Table 2.2 demonstrates the value of $\lim_{t\to\infty} \psi_t$ for some different combinations of values of h and λ (all these combinations satisfy (5) and (6)).

Table 2.2. Probability of being in $w_{q^h q^l, Calm}$ when the game is long enough

$\lim_{t\to\infty} \psi_t$		***h***		
		0.1	**0.2**	**0.25**
$\boldsymbol{\lambda}$	**0.85**	0.787	0.806	0.816
	0.875	0.816	0.833	0.841
	0.9	0.847	0.862	0.870

From Table 2.2 we see that, for example, if $h = 0.2$ and $\lambda = 0.875$, then the probability that each seller or buyer is in the state $w_{q^h q^l, Calm}$ converges to 83.3% if the game is long enough. In other words, sellers and buyers should play $(q^h q^l, Calm)$ 83.3% of the time and play $(q^h q^h, Cry)$ 16.7% of the time in the long run.

2.3.5. How a Nudge Changes Behavior

I consider a "nudge" that makes salient the information that playing $(q^h q^l, Calm)$ Pareto-dominates $(q^h q^h, Cry)$, without limiting their options or changing their economic incentives,[26] and thus make the strategy profile $(q^h q^l, Calm)$ more salient than other profiles. When the implementation of the nudge is common knowledge to all sellers and buyers, the salience of $(q^h q^l, Calm)$ makes this strategy profile a Schelling point.[27] (Schelling, 1980) Therefore, sellers and buyers are predicted to be more likely to play $(q^h q^l, Calm)$ when the nudge is implemented.

2.4. Experimental Design

To empirically test whether the reputation system and/or nudge reduces occurrences of $q^l q^l$ and defensive treatment (and thus improves the welfare of both buyers and sellers), I conduct a laboratory experiment using a 2x2 design. There are four conditions: *Baseline*, *Reputation*, *Nudge* and *Reputation+Nudge*.

The parameters of the game are set as below, which satisfy (1) to (3) as well as (22) so that the 2-period punishment strategy profile is a PPE:

$$\lambda = 0.875; h = 0.2; v = 120; p^h = 80; c^h = 40; p^l = 50; c^l = 0; \beta = 160; \gamma = 20$$

I use the strategy method to elicit sellers' and buyers' decisions: At the beginning of each period, each seller determines in advance a treatment choice contingent on each problem type;

[26] This nudge should not add any new information to sellers and buyers, because the Pareto-efficiency of $(q^h q^l, Calm)$ can be directly inferred from the game. However, it might still help strategically unsophisticated subjects realize that they can be better off from playing $(q^h q^l, Calm)$ and thus it might be still an informational method. My experimental results, however, provide evidence against this channel. I find that when the nudge is present, the proportions of choosing $q^h q^l$ and $q^h q^l$ in early periods of the game are not significantly different from them in the conditions without the nudge. If the nudge were informational, then I would have observed a significantly lower proportion of $q^h q^h$ and higher proportion of $q^h q^l$ from the beginning of the game when the nudge is present. See the relevant experimental results in Sections 2.6.2.2 and 2.6.2.4.

[27] A Schelling point (also known as a focal point) is an action profile people tend to choose by default without communication.

each buyer determines in advance whether to cry or not[28] if and only if the seller chooses a q^l treatment and the treatment fails.

In the *Baseline* condition, there are 8 subjects in each session. 4 subjects are randomly assigned the role of sellers and the other 4 subjects the role of buyers. In each round, one seller is randomly matched with one buyer, and the matching is reshuffled after each round. Each subject plays the game repeatedly for 60 rounds, and starting from Period 61, a random termination rule applies (the game ends with a probability of 10%).[29]

After each pair finishes making decisions in each round, each seller is immediately notified of the buyer's problem type, her treatment choice according to her strategy, whether the treatment succeeded, the buyer's reaction (if available) and her own payoff in the current period. Each buyer is immediately notified of her seller's treatment choice, whether the treatment succeeded, her reaction (if available) and her own payoff in the current period. To mimic a perfect recall setting, each subject can also see a history of the outcome information she herself received at the end of each period.

In the *Reputation* condition, there are only two differences from the *Baseline* condition: First, in every period, each seller's complete history of public signals is available to the buyer matched with this seller. Second, in every period, each seller and buyer are notified of whether there exists any seller-buyer pair in which the seller compensated the buyer in each of the previous periods.

In the *Nudge* condition, each subject is asked to finish an additional comprehension question (in addition to other comprehension questions) before the start of the repeated game[30]. In this comprehension question, each subject is asked to calculate each seller's and buyer's total expected payoffs across 60 periods in two scenarios: (1) When all sellers choose $q^h q^h$ and when all buyers choose Cry; (2) When all sellers choose $q^h q^l$ and when all buyers choose $Calm$. By

[28] To avoid a potential framing effect, *Cry* and *Calm* are framed as *Demand* and *Not Demand* respectively in the experiment.

[29] When analyzing the experimental data, I focus on the first 60 periods because I am most interested in behavior when the discount factor is close to 1. The termination rule starting from Period 61 is mainly used to finish the game.

[30] Subjects are informed that every subject finishes the same comprehension questions.

calculating each seller and buyer's payoffs in these two strategy profiles on their own, the information that $(q^h q^l, Calm)$ Pareto-dominates $(q^h q^h, Cry)$ is made salient, and I mitigate the potential experimenter demand effect from directly reminding them of this piece of information.

In the *Reputation+Nudge* condition, each subject both answers the additional payoff calculation question and has access to the reputation system.

To provide supplementary explanations for possible motivations of subjects' actions, I also ask sellers (buyers) to state the most socially appropriate strategy buyers (sellers) should take (i.e., first-order normative beliefs) and the most socially appropriate strategy buyers (sellers) think they should take (i.e., second-order normative beliefs) after the repeated game.[31] Their risk preferences are elicited through an unincentivized Holt-Laury survey (Holt & Laury, 2002), and their demographic information is also collected.

Table 2.3 below summarizes the procedures of each condition. The experimental instructions can be found in Appendix 2.D.

Table 2.3. Procedures of each condition

Stage	Task	*Baseline*	*Reputation*	*Nudge*	*Reputation+ Nudge*
1	Experimental instructions	Yes	Yes	Yes	Yes
2	Comprehension questions	Yes	Yes	Yes (with the additional payoff calculation question)	Yes (with the additional payoff calculation question)
3	Repeated game	No reputation	With reputation	No reputation	With reputation
4	Post-experiment survey questions (1) Norm belief elicitation questions (2) Risk preference elicitation questions (3) Demographic questions	Yes	Yes	Yes	Yes
5	Final payoff report	Yes	Yes	Yes	Yes

[31] To avoid collecting responses that may suffer from self-serving bias, the bias to justify one's own actions by stating one believes they are appropriate, I do not ask subjects to state the most socially appropriate action they themselves should take.

There are 5 sessions in each of the 4 conditions with a total of 160 subjects.[32] To make the results between different conditions comparable, I pre-generated random numbers to determine the random events in each period for each of the 5 sessions, including the buyer's problem type, whether a sufficient treatment succeeds or not, whether an undertreatment succeeds or not, which seller is matched with which buyer, and whether the game ends after the current period (starting from Period 61). Thus, all conditions have the 5 sessions with the same "quasi-random" events in all periods.

I use zTree (Fischbacher, 2007) to program this experiment. Most subjects are students from the University of Michigan.[33] They are recruited via the online recruitment platform ORSEE (Greiner, 2015). Each subject is only allowed to participate in one session. The experiment is run online through zTree unleashed (Duch et al., 2020). Subjects have the experimental instructions read aloud to them on Zoom.[34] Each session lasts for 75-85 minutes on average. Each subject is paid a show-up fee of $5. The average earnings of each subject are $14.69.

2.5. Hypotheses

In this section, I describe the hypotheses in the experimental context based on my theoretical predictions.

In the *Baseline* condition in which neither the reputation system nor the nudge is present, I predict that $(q^h q^h, Cry)$ is the most common strategy profile played by sellers and buyers, so I have the following hypotheses:

Hypothesis 1.1 (Seller behavior in *Baseline*): In *Baseline*, sellers are most likely to choose $q^h q^h$.

[32] The sample size was determined as follows: The proportions of $q^h q^l$ and Cry are estimated to be 15% in *Baseline* (based on Bonacich et al., 1976) and 57% in *Reputation* (based on Cooper et al., 1996). With $\alpha = 0.05$ and $\beta = 0.80$, the required sample size is 19 sellers/buyers per condition.

[33] A few subjects are alumni of the University of Michigan.

[34] To mitigate potential demographic effects, I ask subjects to turn off their webcams and microphones, and I rename each subject as "Participant X" in the Zoom room so that no one can see any other subject's real name. They can only send private messages to the experimenter but cannot send messages among each other.

Hypothesis 1.2 (Buyer behavior in *Baseline*): In *Baseline*, buyers are most likely to choose Cry.

In the *Reputation* condition, I predict that sellers and buyers are less likely to play $(q^h q^h, Cry)$ and more likely to play $(q^h q^l, Calm)$ than they do in the *Baseline* condition.

Hypothesis 2.1 (Seller behavior in *Reputation* vs. *Baseline*): Sellers in *Reputation* are less likely to choose $q^h q^h$ and more likely to choose $q^h q^l$ than sellers in *Baseline* are.

Hypothesis 2.2 (Buyer behavior in *Reputation* vs. *Baseline*): Buyers in *Reputation* are less likely to choose Cry than buyers in *Baseline* are.

In the *Nudge* condition, I also predict that sellers and buyers are less likely to choose $(q^h q^h, Cry)$ and more likely to choose $(q^h q^l, Calm)$ than they do in the *Baseline* condition.

Hypothesis 3.1 (Seller behavior in *Nudge* vs. *Baseline*): Sellers in *Nudge* are less likely to choose $q^h q^h$ and more likely to choose $q^h q^l$ than sellers in *Baseline* are.

Hypothesis 3.2 (Buyer behavior in *Nudge* vs. *Baseline*): Buyers in *Nudge* are less likely to choose Cry than buyers in *Baseline* are.

In the *Reputation+Nudge* condition, since the two interventions are used together, I predict that sellers and buyers are less likely to choose $(q^h q^h, Cry)$ and more likely to choose $(q^h q^l, Calm)$ than they do in all the other three conditions.

Hypothesis 4.1.1 (Seller behavior in *Reputation+Nudge* vs. *Baseline*): Sellers in *Reputation+Nudge* are less likely to choose $q^h q^h$ and more likely to choose $q^h q^l$ than sellers in *Baseline* are.

Hypothesis 4.1.2 (Buyer behavior in *Reputation+Nudge* vs. *Baseline*): Buyers in *Reputation+Nudge* are less likely to choose Cry than buyers in *Baseline* are.

Hypothesis 4.2.1 (Seller behavior in *Reputation+Nudge* vs. *Reputation*): Sellers in *Reputation+Nudge* are less likely to choose $q^h q^h$ and more likely to choose $q^h q^l$ than sellers in *Reputation* are.

Hypothesis 4.2.2 (Buyer behavior in *Reputation+Nudge* vs. *Reputation*): Buyers in *Reputation+Nudge* are less likely to choose Cry than buyers in *Reputation* are.

Hypothesis 4.3.1 (Seller behavior in *Reputation+Nudge* vs. *Nudge*): Sellers in *Reputation+Nudge* are less likely to choose $q^h q^h$ and more likely to choose $q^h q^l$ than sellers in *Nudge* are.

Hypothesis 4.3.2 (Buyer behavior in *Reputation+Nudge* vs. *Nudge*): Buyers in *Reputation+Nudge* are less likely to choose Cry than buyers in *Nudge* are.

2.6. Results

2.6.1. Behavior and Market Efficiency in the Late Stage (Periods 41-60)

Section 2.6 discusses the experimental results. To simplify my discussion of the repeated game, I divide the first 60 periods, which have a discount factor of 1, into the early (Periods 1-20), middle (Periods 21-40) and late (Periods 41-60) stages.

In Section 2.6.1, I first examine the sellers' and buyers' behaviors in the late stage (Periods 41-60). The results in the late stage show where sellers' and buyers' behaviors converge. Figure 2.5 demonstrates sellers' proportions of $q^h q^h$, $q^h q^l$ and $q^l q^l$ and buyers' proportion of Cry in each condition and compares the likelihood of each action between conditions using Random-effects Logistic regressions.[35] Figure 2.6 shows the average market efficiency[36] in each condition.

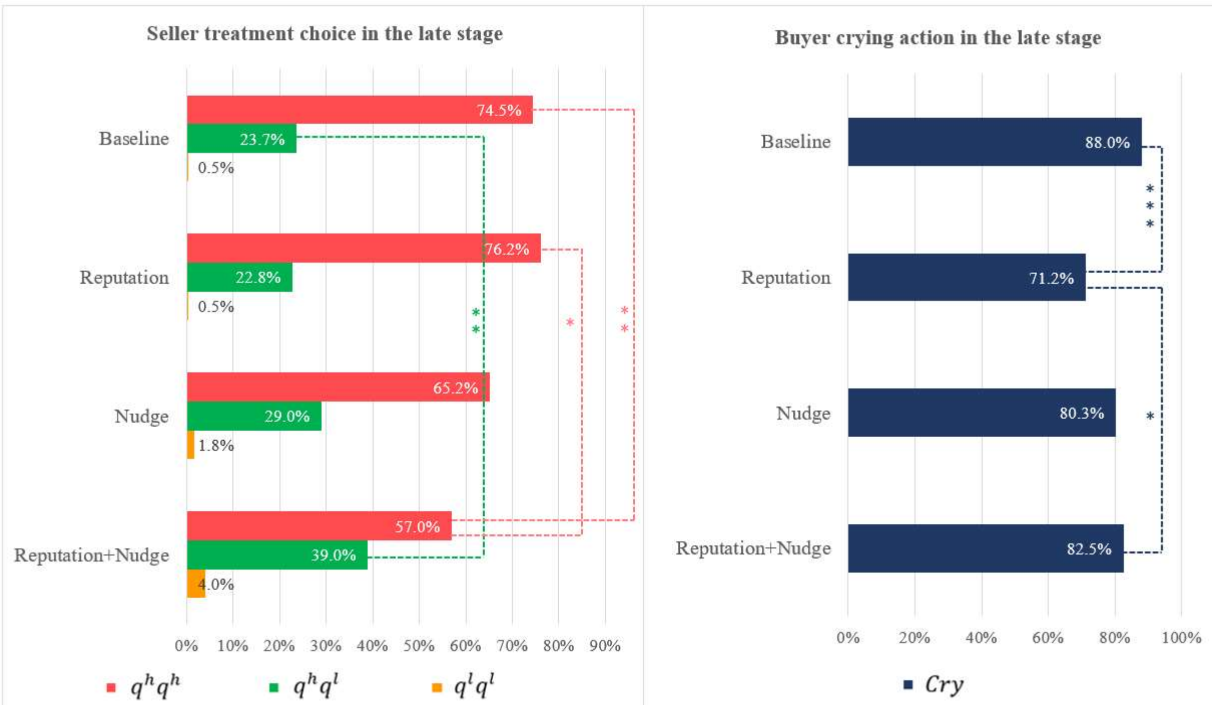

Figure 2.5. Proportions of sellers' treatment choices and buyer crying behavior in the late stage (Periods 41-60)

Notes:

1. The dashed line and stars indicate the p-value for the coefficient on the condition dummy variable in the corresponding random-effects logistic regression (with standard errors adjusted for clustering at the subject level). See Tables 2.B.1.1 to 2.B.1.5 in Appendix 2.B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

---

[35] The proportion of $q^l q^h$ is not included in the analysis in this section, because it is not an interesting action for sellers to choose both theoretically and experimentally. Theoretically, $q^l q^h$ is never a best response regardless of a seller's belief about the buyer's action, and it never leads to a Pareto-efficient outcome regardless of the buyer's action. My experimental data shows that the proportion of $q^l q^h$ is never higher than 5% in any condition in any stage.

[36] Market efficiency = (Sum of payoffs of all sellers and buyers – Minimum sum of total expected payoff) / (Maximum sum of total expected payoff – Minimum sum of total expected payoff)

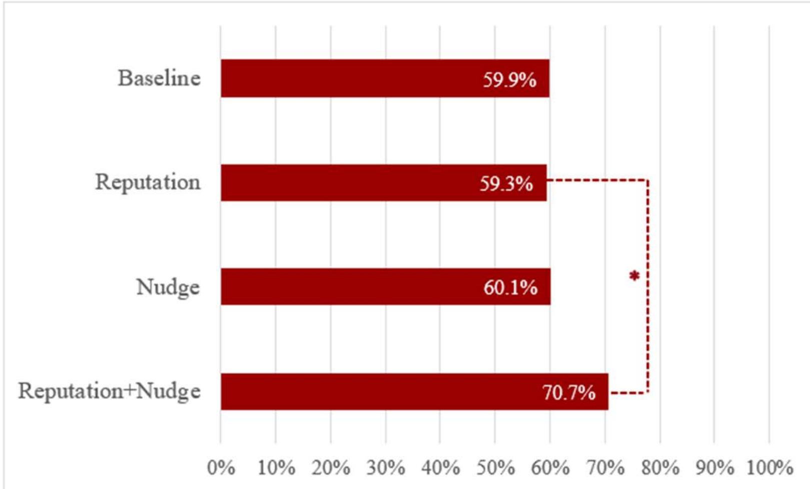

Figure 2.6. Average market efficiency in the late stage (Periods 41-60)

Notes:
1. The dashed line and stars indicate the p-value for the condition dummy variable in the corresponding random-effects linear regression (with standard errors adjusted for clustering at the session level). See Tables 2.B.1.1 to 2.B.1.5 in Appendix 2.B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

2.6.1.1. Behavior in Baseline in the Late Stage

For sellers in *Baseline* in the late stage, 74.5% of sellers' choices of treatment are $q^h q^h$, while 23.7% are $q^h q^l$. Only 0.5% of seller choices of treatment are $q^l q^l$. For buyers in *Baseline*, 88.0% buyer behaviors are Cry. Therefore, I find support for Hypotheses 1.1 and 1.2.

> **Result 1.1 (Seller behavior in *Baseline*):** Sellers in *Baseline* are most likely to choose $q^h q^h$ in the late stage.
>
> **Result 1.2 (Buyer behavior in *Baseline*):** Buyers in *Baseline* are most likely to choose Cry in the late stage.

Therefore, when neither a reputation system nor a nudge is present, sellers and buyers tend to reach the Pareto-dominated perfect Bayesian equilibrium in the late stage. In particular, sellers choose defensive treatment, while buyers resort to crying.

2.6.1.2. Reputation vs. Baseline in the Late Stage

Sellers' treatment choices are not significantly different between *Reputation* and *Baseline*. The proportion of $q^h q^h$ is 76.2% in *Reputation* and 74.5% in *Baseline*. The proportion of $q^h q^l$ is 22.8% in *Reputation* and 23.7% in *Baseline*. The proportions of $q^l q^l$ are 0.5% in both *Reputation* and *Baseline.* There is no significant difference in the likelihood of $q^h q^h$ (p=0.537), $q^h q^l$ (p=0.358) or $q^h q^l$ (p=0.996). I do not find support for Hypothesis 2.1. However, the proportion of crying behavior is 71.2% in *Reputation* and 88.0% in *Baseline*, and the likelihood of buyers' crying behavior is significantly lower in *Reputation* than that in *Baseline* (p=0.007). Hypothesis 2.2 is supported.

Result 2.1 (Seller behavior in *Reputation* vs. *Baseline*): The likelihoods of sellers' $q^h q^h$, $q^h q^l$ and $q^l q^l$ in *Reputation* are not significantly different from them respectively in *Baseline* in the late stage.

Result 2.2 (Buyer behavior in *Reputation* vs. *Baseline*): Buyers in *Reputation* are significantly less likely to choose Cry than buyers in *Baseline* are in the late stage.

There is no significant difference in average market efficiency between *Reputation* and *Baseline* (59.3% vs. 59.9%, p=0.915).

The comparison between *Baseline* and *Reputation* demonstrates that the reputation system alone does not encourage $q^h q^l$ or discourage $q^h q^h$. However, it significantly reduces the proportion of crying behavior, although the proportion is still higher than 70% after this significant reduction. The reputation system alone does not significantly improve market efficiency in the late stage.

2.6.1.3. Nudge vs. Baseline in the Late Stage

Sellers' and buyers' behaviors are not significantly different between *Nudge* and *Baseline* in the late stage. The proportion of $q^h q^h$ is 65.2% in *Nudge* and 74.5% in *Baseline*. The proportion of $q^h q^l$ is 29.0% in *Nudge* and 23.7% in *Baseline*. The proportion of $q^l q^l$ is 1.8% in *Nudge* and 0.5% in *Baseline*. The proportion of Cry is 80.3% in *Nudge* and 88.0% in *Baseline*. There is no significant difference in the likelihood of $q^h q^h$ (p=0.181), $q^h q^l$ (p=0.270), $q^l q^l$ (p=0.336) or Cry (p=0.260). The average market efficiency in *Nudge* in the late stage is 60.1%, which is not significantly different from that in *Baseline* (59.9%, p=0.962).

> **Result 3.1 (Seller behavior in *Nudge* vs. *Baseline*):** The likelihoods of sellers' $q^h q^h$, $q^h q^l$ and $q^l q^l$ in *Nudge* are not significantly different from them respectively in *Baseline* in the late stage.
>
> **Result 3.2 (Buyer behavior in *Nudge* vs. *Baseline*):** The likelihood of buyers' crying behavior in *Nudge* is not significantly different from that in *Baseline* in the late stage.

Therefore, Hypotheses 3.1 and 3.2 are not supported. I thus conclude that nudge alone is insufficient to significantly influence sellers' or buyers' behavior or improve market efficiency in the late stage.

2.6.1.4. Reputation+Nudge vs. Baseline in the Late Stage

The proportion of $q^h q^h$ is 57.0% in *Reputation+Nudge* and 74.5% in *Baseline*, and the likelihood of $q^h q^h$ in *Reputation+Nudge* is significantly higher than that in *Baseline* (p=0.025). The proportion of $q^h q^l$ is 39.0% in *Reputation+Nudge* and 23.7% in *Baseline*, and the likelihood of $q^h q^l$ in *Reputation+Nudge* is significantly lower than that in *Baseline* (p=0.029). The proportion of $q^l q^l$ is 4.0% in *Reputation+Nudge* and 0.5% in *Baseline*, and the likelihood of $q^l q^l$ is not significantly different between the two conditions (p=0.422). These results support Hypothesis 4.1.1. The proportion of Cry is 82.5% in *Reputation+Nudge* and 88.0% in *Baseline*, and there is no significant difference in likelihood of crying behavior between the two conditions (p=0.422). Thus, I do not find support for Hypotheses 4.1.2.

Result 4.1.1 (Seller behavior in *Reputation+Nudge vs. Baseline*): The likelihood of $q^h q^h$ in *Reputation+Nudge* is significantly lower than that in *Baseline*. The likelihood of $q^h q^l$ in *Reputation+Nudge* is significantly higher than that in *Baseline*.

Result 4.1.2 (Buyer behavior in *Reputation+Nudge vs. Baseline*): The likelihood of crying behavior in *Reputation+Nudge* is not significantly different from that in *Baseline* in the late stage.

There is no significant difference in market efficiency between the two conditions (70.7% vs. 59.9%, p=0.122).

2.6.1.5. Reputation+Nudge vs. Reputation in the Late Stage

The proportion of $q^h q^h$ is 57.0% in *Reputation+Nudge* and 76.2% in *Reputation*, and the likelihood of $q^h q^h$ in *Reputation+Nudge* is marginally significantly lower than that in *Reputation* (p=0.071). The proportion of $q^h q^l$ is 39.0% in *Reputation+Nudge* and 22.8% in *Reputation*, and the likelihood of $q^h q^l$ is not significantly different between the two conditions (p=0.168). The proportion of $q^l q^l$ is 4.0% in *Reputation+Nudge* and 0.5% in *Baseline*, and there is no significant difference in likelihood of $q^l q^l$ between the two conditions (p=0.422). I find weak support for Hypothesis 4.2.1. The proportion of crying behavior is 82.5% in *Reputation+Nudge* and 71.2% in *Reputation*, and the likelihood of crying behavior in *Reputation+Nudge* is marginally significantly higher than that in *Reputation* (p=0.085). There is weak support for Hypothesis 4.2.2.

Result 4.2.1 (Seller behavior in *Reputation+Nudge vs. Reputation*): Sellers in *Reputation+Nudge* are marginally significantly less likely to overtreat than they are in *Reputation* in the late stage. The likelihood of $q^h q^l$ in *Reputation+Nudge* is not significantly different from that in *Reputation* in the late stage.

Result 4.2.2 (Buyer behavior in *Reputation+Nudge vs. Reputation*): Buyers in *Reputation+Nudge* are marginally significantly more likely to cry than they are in *Reputation* in the late stage.

The average market efficiency in *Reputation+Nudge* is marginally significantly higher than that in *Reputation* (70.7% vs. 59.3%, p=0.058).

2.6.1.6. Reputation+Nudge vs. Nudge in the Late Stage

Sellers' and buyers' behaviors are not significantly different between *Reputation+Nudge* and *Nudge* in the late stage. The proportion of $q^h q^h$ is 57.0% in *Reputation+Nudge* and 65.2% in *Nudge.* The proportion of $q^h q^l$ is 39.0% in *Reputation+Nudge* and 29.0% in *Nudge.* The proportion of $q^l q^l$ is 4.0% in *Reputation+Nudge* and 1.8% in *Nudge.* The proportion of crying behavior is 82.5% in *Reputation+Nudge* and 80.3% in *Nudge.* There is no significant difference in likelihood of $q^h q^h$ (p=0.366), $q^h q^l$ (p=0.335), $q^l q^l$ (p=0.762) or Cry (p=0.751) in the late stage. Hypotheses 4.3.1, 4.3.2 or 4.3.3 are not supported.

Result 4.3.1 (Seller behavior in *Reputation+Nudge vs. Nudge*): The likelihoods of sellers' $q^h q^h$, $q^h q^l$ and $q^l q^l$ in *Reputation+Nudge* are not significantly different from them respectively in *Nudge* in the late stage.

Result 4.3.2 (Buyer behavior in *Reputation+Nudge vs. Nudge*): The likelihood of crying behavior in *Reputation+Nudge* is not significantly different from that in *Nudge* in the late stage.

The average market efficiency in *Reputation+Nudge* condition is 70.7%, which is not significantly different from that in *Nudge* (60.1%, p=0.117).

2.6.1.7. Summary of Behavior and Market Efficiency in the Late Stage

By examining sellers' and buyers' behavior and market efficiency in the late stage in different treatment conditions, I reach the following conclusions:

1. Most sellers choose $q^h q^h$, while most buyers choose Cry in the *Baseline* condition in which neither the reputation system nor the nudge is present. Most sellers and buyers reach the Pareto-inefficient perfect Bayesian equilibrium.
2. When the reputation system alone is introduced, buyers are significantly less likely to choose Cry, although sellers do not significantly reduce $q^h q^h$ or increase $q^h q^l$.
3. The nudge alone does not significantly change sellers' treatment choices or buyers' behaviors.
4. When both the reputation system and nudge are used, sellers are significantly more likely to choose $q^h q^l$ and significantly less likely to overtreat compared with their behavior in the *Baseline* condition, yet buyers' behaviors are not significantly affected.
5. When the reputation system is already present, introducing the nudge marginally significantly reduce sellers' $q^h q^h$ but also marginally increase buyers' crying behavior. The market efficiency after introducing the nudge is marginally significantly higher than that when only the reputation system is present.
6. When nudge is already present, introducing the reputation system does not significantly affect sellers' treatment choices, buyers' crying behavior or market efficiency.

2.6.2. How Sellers' and Buyers' Behavior Changes Over Time

In this subsection, I examine how sellers' and buyers' behavior change over time and compare the differences in sellers' and buyers' behavior between conditions in three different stages. Recall that sellers and buyers with the reputation system are predicted to play the Pareto-efficient strategy profile $(q^h q^l, Calm)$ most of the time until the public signal LFR is realized (i.e., compensation is realized), while sellers and buyers are predicted to play $(q^h q^h, Cry)$ all the time.

By examining the time trends of sellers' and buyers' behavior, I check whether sellers and buyers generally play the predicted strategy and, if not, how they adjust their behavior over time.

2.6.2.1. General Change of Behavior Over Time

Figure 2.7 summarizes the proportions of $q^h q^h$, $q^h q^l$, $q^l q^l$ and Cry in the early, middle and late stages in all conditions and compares the likelihood of each action between conditions using Random-effects Logistic regressions. Figure 2.8 shows the average market efficiency in the three stages in all conditions.

The proportion of $q^h q^h$ in all four conditions rises over time, while the proportion of $q^h q^l$ in all four conditions drops over time. In the early stage, the proportions of $q^h q^h$ and $q^h q^l$ in all conditions are close to 50-50 split. In the late stage, $q^h q^h$ is played 57%-76% of the time in all conditions, while $q^h q^l$ is only played 23%-39% of the time. The proportion of $q^l q^l$ is less than 9% in the early stage in all conditions, and then drops to less than 5% in the late stage. The proportion of crying stays above 70% in all conditions. There are no clear trends of how average market efficiency change over the three stages.

In the remaining part of this subsection, I compare whether and how the differences in sellers' treatment choices, buyer crying behavior and market efficiency between conditions change over time.

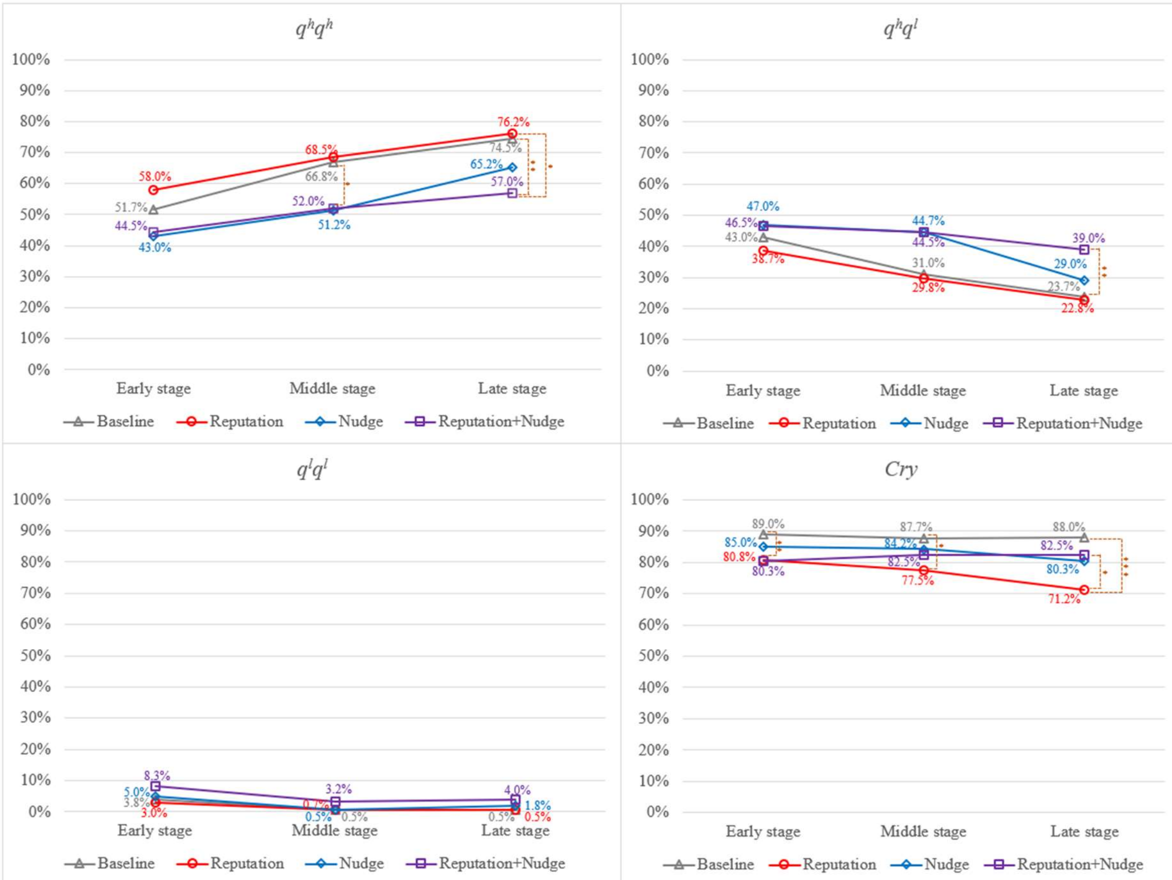

Figure 2.7. Proportions of sellers' treatment choices and buyer crying behavior in three stages

Notes:

1. The dashed line and stars indicate the p-value for the coefficient on the condition dummy variable in the corresponding random-effects logistic regression (with standard errors clustered at the subject level). See Tables 2.B.1.1 to 2.B.3.5 in Appendix 2.B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

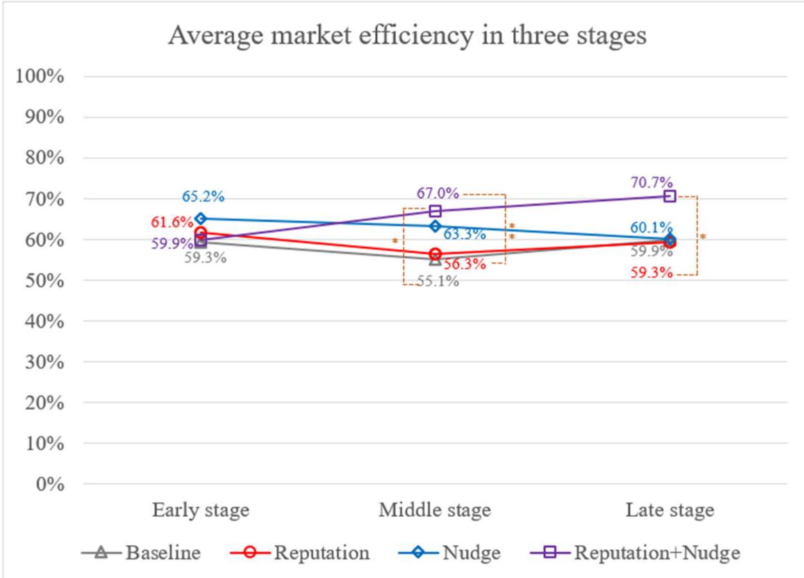

Figure 2.8. Average market efficiency in three stages

Notes:

1. The dashed line and stars indicate the p-value for the condition dummy variable in the corresponding random-effects linear regression (with standard errors adjusted for clustering at the session level). See Tables 2.B.1.1 to 2.B.3.5 in Appendix 2.B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

2.6.2.2. Reputation vs. Baseline

Figure 2.7 shows that the differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Reputation* and *Baseline* are insignificant in the early stage ($q^h q^h$: proportions 58.0% vs. 51.7%, likelihood difference p=0.371; $q^h q^l$: proportions 38.7% vs. 43.0%, likelihood difference p=0.562; $q^l q^l$: proportions 3.0% vs. 3.8%, likelihood difference p=0.465), middle stage ($q^h q^h$: proportions 68.5% vs. 66.8%, likelihood difference p=0.730; $q^h q^l$: proportions 29.8% vs. 31.0%, likelihood difference p=0.807; $q^l q^l$: proportions 0.7% vs. 0.5%, likelihood difference p=0.648), and late stage ($q^h q^h$: proportions 76.2% vs. 74.5%, likelihood difference p=0.537; $q^h q^l$: proportions 22.8% vs. 23.7%, likelihood difference p=0.358; $q^l q^l$: proportions 0.5% vs. 0.5%, likelihood difference p=0.996). The difference in proportion of crying behavior between the two conditions is significant in the early stage (proportions 80.8% vs. 89.0%, likelihood difference p=0.044), marginally significant in the middle stage (proportions 77.5% vs. 87.7%, likelihood difference p=0.053) and significant in the late stage (proportions 71.2% vs. 88.0%, likelihood difference p=0.007). Figure

2.8 shows that the difference in market efficiency between the two conditions is not significant in all three stages (Early stage: 61.6% vs. 59.3%, p=0.837; Middle stage: 56.3% vs. 55.1%, p=0.837; Late stage: 59.3% vs. 59.9%, p=0.915).

The regression results in Table 2.4 demonstrate that the likelihood of $q^h q^h$ in *Baseline* significantly rises over time (Column 1, coefficient = 0.062, p<0.001), and increase rate of $q^h q^h$ in *Reputation* is not significantly different from that in *Baseline* (Column 1, coefficient = -0.0270, p=0.190). The likelihoods of $q^h q^l$ and $q^l q^l$ in *Baseline* significantly decrease over time ($q^h q^l$: Column 2, coefficient = -0.0516, p=0.002; $q^l q^l$: Column 3, coefficient = -0.068, p=0.032). The decrease rates of $q^h q^l$ and $q^l q^l$ in *Reputation* are not significant different from them in *Baseline* respectively ($q^h q^l$: Column 2, coefficient = -0.022, p=0.304; $q^l q^l$: Column 3, coefficient = -0.005, p=0.935). The likelihood of crying behavior in *Reputation* is significantly lower than that in *Baseline* throughout Periods 1-60 (Column 4, coefficient = -1.972, p=0.029). There is no significant change of the likelihood of crying behavior over time in *Baseline* (Column 4, coefficient = -0.003, p=0.606), and the change rate of likelihood of crying behavior in *Reputation* is not significantly different from that in *Baseline* (Column 4, coefficient = -0.014, p=0.269). There is no significant change of market efficiency over time in *Baseline* (Column 5, coefficient = -0.001, p=0.732), and the change rate of market efficiency in *Reputation* is not significantly different from that in *Baseline* (Column 5, coefficient = -0.001, p=0.829).

Table 2.4. Time trends of likelihoods of sellers' treatment choices and market efficiency: *Reputation vs. Baseline* (Random-effects Regressions, Periods 1-60)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	1.035	-0.660	-0.450	-1.972**	0.030
	(1.041)	(0.994)	(1.492)	(0.901)	(0.133)
Period	0.062***	-0.052***	-0.068**	-0.003	-0.001
	(0.016)	(0.017)	(0.032)	(0.007)	(0.002)
Period x Reputation	-0.027	0.022	0.005	-0.014	-0.001
	(0.021)	(0.021)	(0.066)	(0.012)	(0.002)
Constant	-0.546	-0.036	-4.678***	5.227***	0.601***
	(0.780)	(0.752)	(0.989)	(0.833)	(0.091)
Observations	2,400	2,400	2,400	2,400	600

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Result 5.1 (Time trends of sellers' treatment choices: *Reputation vs. Baseline*): The differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Baseline* and *Reputation* are not significant in all three stages. The likelihood of $q^h q^h$ in *Baseline* significantly increases over time. The likelihoods of $q^h q^l$ and $q^l q^l$ significantly decrease over time. The change rates of likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ in *Reputation* are not significantly different from them in *Baseline*.

Result 5.2 (Time trends of buyers' crying behavior in *Reputation vs. Baseline*): The likelihood of crying behavior in *Reputation* is significantly lower than that in *Baseline* in all three stages. The likelihood of crying behavior in *Baseline* does not significantly change over time, and the change rate in *Reputation* is not significantly different from that in *Baseline*.

2.6.2.3. Nudge vs. Baseline

Figure 2.7 shows that the differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Nudge* and *Baseline* are insignificant in the early stage ($q^h q^h$: proportions 43.0% vs. 51.7%, likelihood difference p=0.480; $q^h q^l$: proportions 47.0% vs. 43.0%, likelihood difference p=0.673; $q^l q^l$: proportions 5.0% vs. 3.8%, likelihood difference p=0.453), middle stage ($q^h q^h$: proportions 51.2% vs. 66.8%, likelihood difference p=0.300; $q^h q^l$: proportions 44.7% vs. 31.0%, likelihood difference p=0.372; $q^l q^l$: proportions 0.5% vs. 0.5%, likelihood difference p=0.996), and late stage ($q^h q^h$: proportions 65.2% vs. 74.5%, likelihood difference p=0.181; $q^h q^l$: proportions 29.0% vs. 23.7%, likelihood difference p=0.270; $q^l q^l$: proportions 1.8% vs. 0.5%, likelihood difference p=0.336). The difference in likelihood of crying behavior between the two conditions is not significant in all three stages (Early stage: proportions 85.0% vs. 89.0%, likelihood difference p=0.199; Middle stage: proportions 84.2% vs. 87.7%, likelihood difference p=0.215; Late stage: proportions 80.3% vs. 88.0%, likelihood difference p=0.260). Figure 2.8 demonstrates that the difference in market efficiency between the two conditions is not significant in all three stages (Early stage: 65.2% vs. 59.3%, p=0.617; Middle stage: 63.3% vs. 55.1%, p=0.193; Late stage: 60.1% vs. 59.9%, p=0.962).

The regression results in Table 2.5 demonstrate that the increase rate of likelihood of $q^h q^h$ in *Nudge* is not significantly different from that in *Baseline* (Column 1, coefficient = -0.008, p=0.722). The decrease rates of $q^h q^l$ and $q^l q^l$ in *Reputation* are not significantly different from them in *Baseline* respectively ($q^h q^l$: Column 2, coefficient = 0.009, p=0.698; $q^l q^l$: Column 3, coefficient = 0.023, p=0.679). The change rate of likelihood of crying behavior in *Reputation* is not significantly different from that in *Baseline* (Column 4, coefficient = -0.012, p=0.331). The change rate of market efficiency in *Nudge* is not significantly different from that in *Baseline* (Column 5, coefficient = -0.002, p=0.644).

Table 2.5. Time trends of likelihoods of sellers' treatment choices and market efficiency: *Nudge vs. Baseline* (Random-effects Regressions, Periods 1-60)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-0.971	0.700	-0.392	-1.365	0.098
	(1.238)	(1.207)	(1.527)	(1.121)	(0.145)
Period	0.063***	-0.052***	-0.068**	-0.003	-0.001
	(0.017)	(0.017)	(0.032)	(0.007)	(0.002)
Period x Nudge	-0.008	0.009	0.023	-0.012	-0.002
	(0.022)	(0.023)	(0.055)	(0.013)	(0.004)
Constant	-0.481	-0.139	-4.723***	5.691***	0.601***
	(0.826)	(0.785)	(1.022)	(1.035)	(0.091)
Observations	2,400	2,400	2,400	2,400	600

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Result 6.1 (Time trends of sellers' treatment choices: *Nudge vs. Baseline*): The differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Baseline* and *Nudge* are not significant in all three stages. The change rates of likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ in *Nudge* are not significantly different from them respectively in *Baseline*.

Result 6.2 (Time trends of buyers' crying behavior in *Nudge vs. Baseline*): The difference in likelihood of crying behavior is not significant between *Baseline* and *Nudge* in all three stages. The change rate of likelihood of crying behavior in *Nudge* is not significantly different from that in *Baseline*.

2.6.2.4. Reputation+Nudge vs. Baseline

Figure 2.7 shows that the likelihoods of $q^h q^h$ and $q^h q^l$ in the early stage are not significantly different between *Reputation+Nudge* and *Baseline* ($q^h q^h$: proportions 44.5% vs. 51.7%, likelihood difference p=0.715; $q^h q^l$: proportions 46.5% vs. 43.0%, likelihood difference p=0.876). The difference in $q^h q^l$ is still insignificant in the middle stage (proportions 44.5% vs. 31.0%, likelihood difference p=0.145), but the difference in $q^h q^h$ becomes marginally significant in the middle stage (proportions 52.0% vs. 66.8%, likelihood difference p=0.066). In the late stage, the differences in both $q^h q^h$ and $q^h q^l$ become significant ($q^h q^h$: proportions 57.0% vs. 74.5%, likelihood difference p=0.025; $q^h q^l$: proportions 39.0% vs. 23.7%, likelihood difference p=0.029). In other words, the differences in $q^h q^h$ and $q^h q^l$ between *Baseline* and *Reputation+Nudge* become increasingly significant over time. The difference in proportion of $q^l q^l$ remain insignificant in all three stages (Early stage: proportions 8.3% vs. 3.8%, likelihood difference p=0.339; Middle stage: proportions 3.2% vs. 0.5%, likelihood difference p=0.199; Late stage: proportions 4.0% vs. 0.5%, likelihood difference p=0.422). The difference in likelihood of crying behavior is insignificant in all three stages (Early stage: proportions 80.3% vs. 89.0%, likelihood difference p=0.112; Middle stage: proportions 82.5% vs. 87.7%, likelihood difference p=0.298; Late stage: proportions 82.5% vs. 88.0%, likelihood difference p=0.422). Figure 2.8 shows that the difference in market efficiency is insignificant in the early stage (59.9% vs. 59.3%, p=0.962) or late stage (67.0% vs. 55.1%, p=0.122) but is marginally significantly different in the middle stage (70.7% vs. 59.9%, p=0.053).

The regression results in Table 2.6 shows that the increase rate of likelihood of $q^h q^h$ in *Reputation+Nudge* is significantly slower than it is in *Baseline* (Column 1, coefficient = -0.039, p=0.049); The decline rate of $q^h q^l$ in *Reputation+Nudge* is significantly slower than that in *Baseline* (Column 2, coefficient = 0.037, p=0.062). There is no significant difference in the decrease rate of $q^l q^l$ between the two conditions (Column 3, coefficient = 0.039, p=0.259). There is no significant difference in the change rate of crying behavior (Column 4, coefficient = 0.006, p=0.676) or the change rate of market efficiency (Column 5, coefficient = 0.002, p=0.495) between the two conditions.

Table 2.6. Time trends of likelihoods of sellers' treatment choices and market efficiency: *Reputation+Nudge vs. Baseline* (Random-effects Regressions, Periods 1-60)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation+Nudge	0.020	-0.228	0.496	-1.038	0.011
	(0.999)	(0.925)	(1.003)	(1.129)	(0.147)
Period	0.062***	-0.052***	-0.068**	-0.004	-0.001
	(0.016)	(0.017)	(0.032)	(0.007)	(0.002)
Period x Reputation+Nudge	-0.039**	0.037*	0.039	0.006	0.002
	(0.020)	(0.020)	(0.034)	(0.015)	(0.003)
Constant	-0.546	-0.024	-4.510***	6.194***	0.601***
	(0.779)	(0.749)	(0.881)	(1.196)	(0.091)
Observations	2,400	2,400	2,400	2,400	600

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Result 7.1 (Time trends of sellers' treatment choices in *Reputation+Nudge vs. Baseline*): The difference in likelihood of $q^h q^h$ between *Baseline* and *Reputation+Nudge* is not significant in the early stage. In the middle stage, the likelihood of $q^h q^h$ is marginally significant higher than that in *Baseline* in the middle stage and significant higher in the late stage. The increase rate of $q^h q^h$ in *Reputation+Nudge* is significantly slower than that in *Baseline*. The difference in likelihood of $q^h q^l$ between *Baseline* and *Reputation+Nudge* is not significant in the early or middle stage, but significant in the late stage. The decrease rate of $q^h q^l$ in the *Reputation+Nudge* condition is marginally significantly slower than that in the *Baseline* condition.

Result 7.2 (Time trends of buyers' crying behavior in *Reputation+Nudge vs. Baseline*): The difference in likelihood of crying behavior is not significant between *Baseline* and *Reputation+Nudge* in all three stages. The change rate of likelihood of crying behavior in *Reputation+Nudge* is not significantly different from that in *Baseline*.

2.6.2.5. Reputation+Nudge vs. Reputation

Figure 2.7 shows that the likelihood of $q^h q^h$ between the two conditions are not significantly different in the early (proportions 44.5% vs. 58.0%, likelihood difference p=0.160) or middle stage (proportions 52.0% vs. 68.5%, likelihood difference p=0.106), but the difference becomes marginally significant in the late stage (proportions 57.0% vs. 76.2%, likelihood difference p=0.071). The difference in likelihood of $q^h q^l$ remains insignificant in three stages (Early stage: proportions 46.5% vs. 38.7%, likelihood difference p=0.392; Middle stage: proportions 44.5% vs. 29.8%, likelihood difference p=0.195; Late stage: proportions 39.0% vs. 22.8%, likelihood difference p=0.168). The difference in likelihood of $q^l q^l$ is insignificant in three stages (Early stage: proportions 8.3% vs. 3.0%, p=0.129; Middle stage: proportions 3.2% vs. 0.7%, likelihood difference p=0.309; Late stage: proportions 4.0% vs. 0.5%, likelihood difference p=0.422). The difference in likelihood of crying behavior is insignificant in the early (proportions 80.3% vs. 80.8%, likelihood difference p=0.605) and middle stages (proportions 82.5% vs. 77.5%, likelihood difference p=0.429) but becomes marginally significant in the late stage (proportions 82.5% vs. 71.2%, likelihood difference p=0.085). Figure 2.8 shows that the difference in market efficiency is insignificant in the early (59.9% vs. 61.6%, p=0.898), significant in the middle stage (67.0% vs. 56.3%, p=0.035) and marginally significant in the late stage (70.7% vs. 59.3%, p=0.058).

The regression results in Table 2.7 shows that the likelihood of $q^h q^h$ in *Reputation* significantly increases over time (Column 1, coefficient = 0.034, p=0.007), and the increase rate of $q^h q^h$ in *Reputation+Nudge* is not significantly different from that in *Reputation* (Column 1, coefficient = -0.012, p=0.491). The likelihood of $q^h q^l$ in *Reputation* significantly decreases over time (Column 2, coefficient = -0.030, p=0.019), and the decrease rate of $q^h q^l$ in *Reputation+Nudge* is not significantly different from that in *Reputation* (Column 2, coefficient =

0.016, p=0.346). The likelihood of $q^l q^l$ in *Reputation* does not significantly change over time (Column 3, coefficient = -0.063, p=0.271), and the change rate of $q^l q^l$ in *Reputation+Nudge* is not significantly different from that in the *Reputation* condition (Column 3, coefficient = 0.034, p=0.568). The likelihood of crying behavior in *Reputation* marginally significantly decreases over time (Column 4, coefficient = -0.017, p=0.099), and the decrease rate in *Reputation+Nudge* is not significantly different from that in the *Reputation* condition (Column 4, coefficient = 0.020, p=0.240). There is no significant change of market efficiency in *Reputation* over time (Column 5, coefficient = -0.001, p=0.557), and the change rate in *Reputation+Nudge* is not significantly different from that in *Reputation* (Column 5, coefficient = 0.003, p=0.403).

Table 2.7. Time trends of likelihoods of sellers' treatment choices and market efficiency: *Reputation+Nudge vs. Reputation* (Random-effects Regressions, Periods 1-60)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-0.929	0.387	1.008	0.762	-0.019
	(0.874)	(0.791)	(1.442)	(1.032)	(0.150)
Period	0.034***	-0.030**	-0.063	-0.017*	-0.001
	(0.013)	(0.013)	(0.057)	(0.010)	(0.002)
Period x Nudge	-0.012	0.016	0.034	0.020	0.003
	(0.017)	(0.017)	(0.059)	(0.017)	(0.003)
Constant	0.383	-0.588	-5.158***	3.127***	0.631***
	(0.650)	(0.618)	(1.331)	(0.747)	(0.097)
Observations	2,400	2,400	2,400	2,400	600

Notes:
1. The omitted reference condition is *Reputation*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Result 8.1 (Time trends of sellers' treatment choices in *Reputation+Nudge vs. Reputation)*: The difference in likelihood of $q^h q^h$ between *Reputation* and *Reputation+Nudge* is not significant in the early or middle stage, but the likelihood of $q^h q^h$ in *Reputation+Nudge* becomes marginally significantly higher than that in *Reputation* in the late stage. The likelihood of $q^h q^h$ in *Reputation* significantly increases over time, and the increase rate of $q^h q^h$ in *Reputation+Nudge* is not significantly different from that in *Reputation*. The difference in likelihood of $q^h q^l$ between *Baseline* and *Reputation+Nudge* is not significant in all three stages. The likelihood of $q^h q^l$ in *Reputation* significantly decreases over time, and the decrease rate of $q^h q^l$ in the *Reputation+Nudge* condition is not significantly different from that in the *Reputation* condition.

Result 8.2 (Time trends of buyers' crying behavior in *Reputation+Nudge vs. Reputation*): The difference in likelihood of crying behavior is not significant between *Baseline* and *Reputation+Nudge* in the early or middle stage, but the likelihood in *Reputation+Nudge* becomes marginally significantly higher than that in *Reputation* in the late stage. The likelihood of crying behavior in *Reputation* marginally significantly decreases over time, and the decrease rate in *Reputation+Nudge* is not significantly different from that in *Reputation*.

2.6.2.6. Reputation+Nudge vs. Nudge

Figure 2.7 shows that the differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Nudge* and *Reputation+Nudge* are not significant in the early stage ($q^h q^h$: proportions 44.5% vs. 43.0%, likelihood difference p=0.682; $q^h q^l$: proportions 46.5% vs. 47.0, likelihood difference p=0.768; $q^l q^l$: proportions 8.3% vs. 5.0%, likelihood difference p=0.138), middle stage ($q^h q^h$: proportions 52.0% vs. 51.2%, likelihood difference p=0.916; $q^h q^l$: proportions 44.5% vs. 44.7%, likelihood difference p=0.981; $q^l q^l$ proportions 3.2% vs. 0.5%, likelihood difference p=0.199) and late stage ($q^h q^h$: proportions 57.0% vs. 65.2%, likelihood difference p=0.366; $q^h q^l$: proportions 39.0% vs. 29.0%, likelihood difference p=0.335; $q^l q^l$: proportions 4.0% vs. 1.8%, likelihood difference p=0.762). The difference in likelihood of crying behavior between the two conditions is not significant in all three stages (Early stage: proportions 80.3% vs. 85.0%, likelihood difference p=0.795; Middle stage: proportions 82.5% vs. 84.2%, likelihood difference p=0.879; Late stage: proportions 82.5% vs. 80.3%, likelihood difference p=0.751). Figure 2.8 demonstrates that the difference in market efficiency between the two conditions is not significant in all three stages (Early stage: 59.9% vs. 65.2%, p=0.706; Middle stage: 67.0% vs. 63.3%, p=0.509; Late stage: 70.7% vs. 60.1%, likelihood difference p=0.117).

The regression results in Table 2.8 demonstrate that the likelihood of $q^h q^h$ in *Nudge* significantly increases over time (Column 1, coefficient = 0.054, p<0.001), and the increase rate of $q^h q^h$ in *Reputation+Nudge* is marginally significantly lower than that in *Nudge* (Column 1, coefficient = -0.031, p=0.085). The likelihood of $q^h q^l$ in *Nudge* significantly decreases over time (Column 2, coefficient = -0.043, p=0.006), and the decrease rate of $q^h q^l$ in *Reputation+Nudge* is not significantly different from that in *Nudge* (Column 2, coefficient = 0.029, p=0.133). The change rate of $q^l q^l$ in *Reputation+Nudge* is not significantly different from that in *Nudge* (Column 3, coefficient = 0.016, p=0.734). The change rate of likelihood of crying behavior in *Reputation+Nudge* is not significantly different from that in *Nudge* (Column 4, coefficient = 0.018, p=0.280). The change rate of market efficiency in *Reputation+Nudge* is not significantly different from that in *Nudge* (Column 5, coefficient = 0.004, p=0.324).

Table 2.8. Time trends of likelihoods of sellers' treatment choices and market efficiency: *Reputation+Nudge vs. Nudge*
(Random-effects Regressions, Periods 1-60)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	0.921	-0.846	0.948	0.183	-0.087
	(1.078)	(1.039)	(1.431)	(1.180)	(0.162)
Period	0.054***	-0.043***	-0.046	-0.016	-0.002
	(0.014)	(0.016)	(0.045)	(0.011)	(0.003)
Period x Reputation	-0.031*	0.029	0.016	0.018	0.004
	(0.018)	(0.019)	(0.047)	(0.017)	(0.004)
Constant	-1.438*	0.562	-5.119***	4.142***	0.699***
	(0.866)	(0.862)	(1.222)	(0.800)	(0.113)
Observations	2,400	2,400	2,400	2,400	600

Notes:
1. The omitted reference condition is *Nudge*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Result 9.1 (Time trends of sellers' treatment choices: *Reputation+Nudge vs. Nudge*): The differences in likelihoods of $q^h q^h$, $q^h q^l$ and $q^l q^l$ between *Baseline* and *Nudge* are not significant in all three stages. The likelihood of $q^h q^h$ in *Nudge* significantly increases over time, and the increase rate of $q^h q^h$ in *Reputation+Nudge* is marginally significantly lower than that from that in *Nudge.* The likelihood of $q^h q^l$ in *Nudge* significantly decreases over time, and the decrease rate of $q^h q^l$ in *Reputation+Nudge* is not significantly different from that in *Nudge*.

Result 9.2 (Time trends of buyers' crying behavior in *Reputation+Nudge vs. Nudge*): The difference in likelihood of crying behavior is not significant between *Baseline* and *Nudge* in all three stages. The change rate of likelihood of crying behavior in *Reputation+Nudge* is not significantly different from that in *Nudge*.

2.6.2.7. Summary of How Sellers' and Buyers' Behavior Changes Over Time

In Subsection 2.6.2, I compare sellers' treatment choices, buyers' crying behavior and total market payoffs in three stages and the time trends among different conditions. I find the following significant results.

1. In *Baseline*, *Reputation* and *Nudge*, the likelihood of $q^h q^h$ significantly increases over time, while the likelihood of $q^h q^l$ significantly decreases over time.
2. In *Reputation+Nudge*, the likelihood of $q^h q^h$ increases at a slower rate while the likelihood of $q^h q^l$ decreases at a slower rate over time. Because of the slower change rates, the difference in likelihoods of $q^h q^h$ and $q^h q^l$ between *Reputation+Nudge* and other conditions (especially *Baseline*) become more significant in the late stage.
3. The market efficiency in *Reputation+Nudge* tends to become significantly higher than that in *Reputation* or *Baseline* in the middle and late stages.
4. The likelihood of crying behavior in *Reputation* is significantly lower than that in *Baseline* throughout all 60 periods. The likelihood of crying behavior in *Reputation* marginally significantly decreases over time.

2.6.3. Analysis of Buyers' Repeated Game Strategy: How Buyers React to Sellers' Treatment History

The analysis in Section 2.6.2 shows how sellers and buyers adjust their behaviors over time. Sellers tend to increase the likelihood of $q^h q^h$ and decrease the likelihood of $q^h q^l$ over time. Considering the fact that the likelihood of crying behavior is higher than 70% in all three stages, sellers' reactions are consistent with our intuition and my prediction: As there are more realizations of crying behavior over time, sellers become more likely to stop offering $q^h q^l$ and switch to $q^h q^h$ to punish buyers for their reluctance to choose $Calm$.

However, how buyers adjust their behavior over time when the reputation system is present is not consistent with my prediction and requires more discussion. In the *Reputation* condition, most buyers do not start with $Calm$ but start with Cry, and the likelihood of Cry decreases over time, even though the likelihood of sellers' $q^h q^h$ increases and the likelihood of $q^h q^l$ decreases over time.[37] In the *Reputation+Nudge* condition, the likelihood of Cry no longer decreases, when the increase rate of sellers' $q^h q^h$ and the decrease rate of $q^h q^l$ are slower. Buyers seem to play Cry less frequently when the likelihood of $q^h q^h$ is high and the likelihood of $q^h q^l$ is low. When the likelihood of $q^h q^h$ is lower and the likelihood of $q^h q^l$ is higher, we do not see a decline of the likelihood of Cry.

In order to check whether buyers are less likely to "cry" when they observe a higher likelihood of $q^h q^h$ from sellers when the reputation system is present, I regress whether each buyer chooses Cry in each period (excluding Period 1) on the matched seller's proportion of q^h treatment before that period in *Reputation* and *Reputation+Nudge*.

Table 2.9. Correlation between crying behavior and the matched seller's historical proportion of q^h in *Reputation* and *Reputation+Nudge* (Random-effects Logistic Regression, Periods 2-60)

VARIABLES	Cry
Matched seller's historical proportion of q^h	-1.143**
	(0.522)
Constant	4.010***
	(0.764)
Observations	2,360

Notes:
1. Standard errors (in parentheses) are adjusted for clustering at the subject level.
2. *** p<0.01, ** p<0.05, * p<0.1

The result in Table 2.9 demonstrates that a buyer in *Reputation* and *Reputation+Nudge* is significantly less likely to choose Cry when the matched seller's historical proportion of q^h is higher (coefficient = -1.143, p=0.029).[38]

[37] Recall that my predicted Pareto-efficient PPE is that buyers should start with $Calm$ and will perpetually switch to Cry if crying behavior is realized.

[38] I also run the same regression for buyers in *Baseline* and *Nudge*. As expected, there is no significant correlation between a buyer's crying behavior and the matched seller's historical proportion of q^h. See the regression result in Table 2.B.4.1.

Result 10 (Correlation between buyers' crying behavior and the matched seller's treatment choice in *Reputation* and *Reputation+Nudge*): When the reputation system is introduced (i.e., in *Reputation* and *Reputation+Nudge*), a buyer is significantly less likely to choose Cry when the matched seller's historical proportion of q^h is higher.

Result 10 explains why the likelihood of crying is only significantly lower in *Reputation* but not in *Reputation+Nudge*: When the reputation system is present, a buyer is less likely to play Cry only when the seller matched with her chooses $q^h q^h$ frequently (which is the case for most sellers in *Reputation*). When the matched seller's likelihood of $q^h q^h$ is relatively lower and the likelihood of $q^h q^l$ is higher (which is the case for sellers in *Reputation+Nudge*), the buyer will see a lower proportion of q^h and a higher proportion of q^l from the matched seller, and then she may be unwilling to reduce her likelihood of Cry.

2.6.4. Subjects' Normative Belief

Results in previous subsections demonstrate subjects' behavior in the game. In this subsection, I present their belief about the normative behavior in the game, which provides insight into subjects' potential motives behind their behavior.

Figure 2.9 demonstrates the proportions of sellers and buyers with different normative beliefs in all conditions. At an aggregate level, 65.0% sellers and 71.3% buyers believe that $q^h q^l$ is the most socially appropriate behavior for sellers to take, while 23.8% sellers and 25.1% buyers believe that $q^h q^h$ is most socially appropriate. On the other hand, 67.6% sellers and 72.6% buyers believe that it is most socially appropriate for buyers to choose Cry. At the level of strategy profile, most sellers and buyers believe that it is most socially appropriate for sellers to play $q^h q^l$ but it is also most socially appropriate for buyers to play Cry (42.5% sellers and 51.3% buyers). Only around 20% sellers and buyers believe that the Pareto-efficient strategy profile $(q^h q^l, Calm)$ is the most socially appropriate one (22.5% sellers and 20.0% buyers). There are also around 20% of sellers and buyers who believe that the stage-game perfect Bayesian equilibrium $(q^h q^h, Cry)$ is the most socially appropriate one (17.5% sellers and 21.3% buyers).

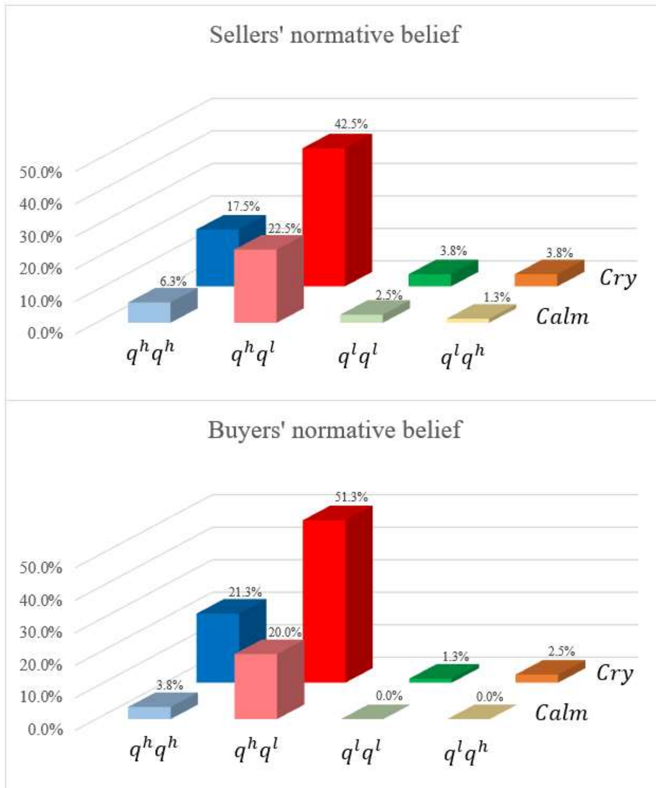

Figure 2.9. Subjects' belief about the normative behavior

These results suggest that most subjects agree that $q^h q^l$ treatment, which maximizes buyers' expected payoff when buyers choose $Calm$, is the most socially appropriate behavior for sellers. This might explain the fact that around 40%-50% sellers in all conditions play $q^h q^l$ in the early stage of the game. However, surprisingly most subjects, including most sellers, believe that Cry is buyers' most socially appropriate behavior. This might explain why most buyers start by playing Cry in the early stage, and the proportions of Cry in all three stages in all conditions are never lower than 70%.

In addition, from the result that most sellers and buyers regard $(q^h q^l, Cry)$, rather than $(q^h q^l, Calm)$, to be the most socially appropriate strategy profile, one might conclude that most people believe that it is still socially appropriate for buyers to play Cry even if sellers are playing the most socially appropriate behavior $q^h q^l$.

2.7. Discussion and Conclusion

In this paper, I discuss inefficiency in credence goods markets where a sufficient treatment that maximizes buyers' expected utility does not guarantee a 100% success rate. I predict that in the one-shot interaction, sellers will choose overtreatment to minimize the probability of treatment failure if the compensation from crying behavior is large enough. In order to improve market efficiency, I consider a reputation system and a behavioral nudge. I show that when there is a reputation system which makes the history of seller treatment history and buyers' aggregate history available, there exists a Pareto-efficient perfect public equilibrium in which sellers will frequently choose the sufficient treatment strategy and buyers will not engage in crying behavior in most cases. I also predict that sellers and buyers are more likely to play the Pareto-efficient strategy profile when I introduce the nudge in which I make salient the fact that a sufficient treatment strategy and not crying lead to a Pareto-efficient outcome.

To test these predictions, I conduct a laboratory experiment using a 2x2 design. At the aggregate level, I find that in *Baseline*, most sellers choose the overtreatment strategy $q^h q^h$ and most buyers engage in crying behavior in the late stage of the game. In *Reputation*, sellers' behavior is not significantly different from that in *Baseline*, while buyers are significantly less likely to engage in crying behavior throughout the game. In *Nudge*, sellers' and buyers' behavior are not significantly different from those in *Baseline*, so introducing the nudge alone is insufficient to change sellers' or buyers' behavior. In *Reputation+Nudge*, sellers' convergence to the overtreatment strategy $q^h q^h$ and decline of choosing the sufficient treatment strategy $q^h q^l$ are significantly slower than those in *Baseline*, which results in the significantly lower likelihood of the overtreatment strategy $q^h q^h$ and the significantly higher likelihood of the sufficient treatment strategy $q^h q^l$ in the late stage relative to *Baseline*. Due to the relatively higher likelihood of the sufficient treatment strategy, the market efficiency in *Reputation+Nudge* is (marginally) significantly higher than that in *Baseline* and *Reputation* in the middle and late stages. Moreover, in all conditions, the proportion of the seller's undertreatment strategy $q^l q^l$ never exceeds 8.3% in any stage, while the proportion of the buyer's crying behavior is always higher than 70% in any stage. Therefore, for the vast majority of cases, buyers' crying behavior does not punish sellers for their undertreatment strategy but is used after bad luck from a sufficient treatment strategy.

Sellers' repeated game strategy tends to be closer to my theoretical predictions than buyers' repeated game strategy. As I predict, many sellers start with the sufficient treatment strategy $q^h q^l$ in the early stage and then switch to the overtreatment strategy $q^h q^h$ in later stages as more compensations are realized. Interestingly, when both the reputation system and nudge are used, sellers will be more lenient with buyers' crying behavior and keep playing the sufficient treatment strategy $q^h q^l$ in later stages of the game. Therefore, the reputation system and the behavioral nudge are complements that can significantly reduce sellers' overtreatment and increase sufficient treatment. Put differently, the effect of the behavioral nudge, which makes sufficient treatment strategy a salient option, is only significant when sellers can see buyers' aggregate history and their own individual history is visible to the buyer. The effect of the reputation system is only significant when the sufficient treatment strategy is made salient to sellers.

As for buyers' repeated game strategy, in *Reputation* and *Reputation+Nudge* where the reputation system is available, only a small fraction of buyers are willing to choose $Calm$ in the early stage, and the proportion of $Calm$ remains lower than 30% in all conditions in all stages. This proportion is significantly lower than my predicted likelihood of 83.3%. In addition, I find that buyers are significantly less likely to choose Cry when the matched seller's historical proportion of q^h is higher. These results have the following implications. First, it explains why the likelihood of crying behavior in *Reputation* is significantly lower than that in *Baseline*, but the likelihood in *Reputation+Nudge* is not. Buyers are only willing to stop "crying" when most sellers overtreat. However, due to the high likelihood of overtreatment, this reduction of crying behavior in *Reputation* is unable to improve the market efficiency. Second, considering the fact that the proportion of the undertreatment strategy $q^l q^l$ is never higher than 8.3% in any stage, the negative correlation between the likelihood of Cry and q^h treatment suggests that buyers tend to “overreact” to the matched seller’s q^l treatment choice, which turns out to be sufficient treatment in most cases.

Subjects’ elicited normative belief may supplement our understanding of the motives of sellers’ and buyers’ behavior. First, it may explain why the proportion of crying behavior is always higher than 70% through all conditions. Second, the fact that two-thirds of sellers regard crying to be the most socially appropriate buyer action may explain why most sellers still overtreat in *Reputation*, as overtreatment is the only way to defend themselves from crying. Only when a behavioral nudge, which draws sellers’ attention to the potential benefit from playing sufficient treatment, is used in addition to the reputation system will sellers be encouraged to keep providing sufficient treatment. Third, sufficient treatment being the most common belief from the perspective of buyers also suggests that buyers understand and believe that the sufficient treatment strategy is the best option for themselves. Therefore, risk aversion or an outcome-oriented preference (i.e., buyers only care about whether the treatment succeeds but not the payoff) might not be good explanations for buyers’ high frequency of crying behavior. Fourth, the “unfair” normative belief shows that people tend to be partial to buyers who are considered to be the “weaker” side due to the lack of information in such credence goods markets. Sellers are expected to take more social responsibility than buyers are.

From the perspective of policy implications, this study shows that a feasible reputation system, which makes each seller’s treatment history and buyers’ aggregate history publicly visible, is theoretically able to lead to a Pareto-improved outcome. The experimental results demonstrate that this reputation system along with a behavioral nudge that makes the Pareto-efficient outcome salient can significantly reduce sellers’ defensive treatment and weakly improve the market efficiency in the long run, but it is insufficient to significantly reduce crying behavior. In order to significantly reduce crying behavior, we might need to alleviate the social bias against sellers and towards buyers.

It should be noted that sellers and buyers in real-life credence goods markets may behave more extremely than they do in this context-neutral laboratory experiment. For example, it is reasonable to conjecture that patients' likelihood of engaging in crying behavior can be even higher, considering the fact that their loss after a treatment failure is not only monetary but also physical and emotional. Therefore, future work may want to investigate how sellers and buyers behave in a controlled field setting.

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Appendices

2.A. Proof of Propositions

2.A.1. Proposition 1: The 2-period punishment hybrid strategy profile described by the automaton in Figure 2.6 is a PPE, if (1) to (4) are satisfied, δ is sufficiently large and the following additional conditions are met:

$$\begin{cases} \delta(1+\delta)(1-h)(2\lambda-1)-1 \geq 0 \\ \delta(1+\delta)(1-h)h(2\lambda-1)+(1-2h) \geq 0 \end{cases}$$

Proof:

To simplify notations, I use the following shortcuts for strategies: HL denotes $q^h q^l$; HH denotes $q^h q^h$; LL denotes $q^l q^l$; LH denotes $q^l q^h$; R denotes $Calm$; M denotes $Calm$. Therefore, $w_{q^h q^l,Calm}$ is rewritten as $w_{HL,M}$; $w_{q^h q^h,Cry}$ is rewritten as $w_{HH,R}$; $w'_{q^h q^h,Cry}$ is rewritten as $w'_{HH,R}$; $w''_{q^h q^h,Cry}$ is rewritten as $w''_{HH,R}$.

2.A.1.1. The $w_{HL,M}$ state:

2.A.1.1.1. The seller

The seller's average discounted values in the $w_{HL,M}$, $w_{HH,R}$ and $w'_{HH,R}$ states are:

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta\big[(1-h)(1-\lambda)V_s(w_{HH,R}) + \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\big] \quad (7)$$

$$V_s(w_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w'_{HH,R}) \quad (8)$$

$$V_s(w'_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w_{HL,M}) \quad (9)$$

From (8) and (9), I know that:

$$V_s(w_{HH,R}) = (1-\delta)\pi^h + \delta\big[(1-\delta)\pi^h + \delta V_s(w_{HL,M})\big]$$

$$= (1-\delta)\pi^h + \delta(1-\delta)\pi^h + \delta^2 V_s(w_{HL,M}) = (1+\delta)(1-\delta)\pi^h + \delta^2 V_s(w_{HL,M}) \quad (10)$$

Plug (10) into (7):

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l]$$

$$+ \delta\big[(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h + \delta^2(1-h)(1-\lambda)V_s(w_{HL,M})$$

$$+ \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\big]$$

$$= (1-\delta)[h\pi^h + (1-h)\pi^l]$$

$$+ \delta\Big[(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h$$

$$+ V_s(w_{HL,M})[\delta^2(1-h)(1-\lambda) + 1 - (1-h)(1-\lambda)]\Big]$$

$$= (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h$$

$$+ \delta[1-(1+\delta)(1-\delta)(1-h)(1-\lambda)]V_s(w_{HL,M})$$

$$\Rightarrow (1-\delta)[1+\delta(1+\delta)(1-h)(1-\lambda)]V_s(w_{HL,M})$$

$$= (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta(1+\delta)(1-\delta)(1-h)(1-\lambda)\pi^h$$

$$\Rightarrow V_s(w_{HL,M}) = \frac{h\pi^h + (1-h)\pi^l + \delta(1+\delta)(1-h)(1-\lambda)\pi^h + \pi^h - \pi^h}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \tag{11}$$

$$\Rightarrow V_s(w_{HH,R}) = (1+\delta)(1-\delta)\pi^h + \delta^2\left(\pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right)$$

$$= (1-\delta^2)\pi^h + \delta^2\pi^h + \frac{\delta^2(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \pi^h + \frac{\delta^2(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \tag{12}$$

The seller's average discounted value of taking a one-shot deviation to HH in the state $w_{HL,M}$ is:

$$g_s(w_{HL,M}, HH) = (1-\delta)\pi^h + \delta V_s(w_{HL,M})$$

$$= (1-\delta)\pi^h + \delta\pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \tag{13}$$

$$V_s(w_{HL,M}) - g_s(w_{HL,M}, HH)$$
$$= \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} - \frac{\delta(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$
$$= (1-\delta)\cdot\frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} > 0 \tag{14}$$

Thus, the seller does not have the incentive to have a one-shot deviation to HH in the state $w_{HL,M}$.

The seller's average discounted value of taking a one-shot deviation to LL in the state $w_{HL,M}$ is:

$$g_s(w_{HL,M}, LL) = (1-\delta)\pi^l$$
$$+ \delta\big[(1-(1-h)\lambda-(1-\lambda)h)V_s(w_{HH,R})$$
$$+ \big((1-h)\lambda+(1-\lambda)h\big)V_s(w_{HL,M})\big] \tag{15}$$

$$\Rightarrow V_s(w_{HL,M}) - g_s(w_{HL,M}, LL)$$
$$= (1-\delta)(-h\Delta\pi)$$
$$+ \delta\big\{[(1-h)(1-\lambda) - 1 + (1-h)\lambda + (1-\lambda)h]V_s(w_{HH,R})$$
$$+ [1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h]V_s(w_{HL,M})\big\}$$

$$= (1-\delta)(-h\Delta\pi)$$

$$+ \delta\left\{[(1-h)(1-\lambda) - 1 + (1-h)\lambda + (1-\lambda)h]\left(\pi^h + \frac{\delta^2(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right)\right.$$

$$\left. + [1-(1-h)(1-\lambda) - (1-h)\lambda - (1-\lambda)h]\left(\pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right)\right\}$$

$$= (1-\delta)(-h\Delta\pi) + \delta[1-(1-h)(1-\lambda) - (1-h)\lambda - (1-\lambda)h]$$

$$\cdot \frac{(1-\delta^2)(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= (1-\delta)\Delta\pi\left[\frac{\delta[1-(1-h)(1-\lambda) - (1-h)\lambda - (1-\lambda)h](1+\delta)(1-h)}{1+\delta(1+\delta)(1-h)(1-\lambda)} - h\right]$$

$$= (1-\delta)\Delta\pi$$

$$\cdot \frac{\delta(1+\delta)(1-h)[1-(1-h)(1-\lambda) - (1-h)\lambda - (1-\lambda)h] - h - h\delta(1+\delta)(1-h)(1-\lambda)}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= (1-\delta)\Delta\pi \cdot \frac{\delta(1+\delta)(1-h)[1-(1-h)(1-\lambda) - (1-h)\lambda - (1-\lambda)h - 2(1-\lambda)h] - h}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= (1-\delta)\Delta\pi \cdot \frac{\delta(1+\delta)(1-h)(2h\lambda - h) - h}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= (1-\delta)\Delta\pi \cdot \frac{h[\delta(1+\delta)(1-h)(2\lambda-1) - 1]}{1+\delta(1+\delta)(1-h)(1-\lambda)} \tag{16}$$

Since we know that $(1-\delta)\Delta\pi > 0$, $1+\delta(1+\delta)(1-h)(1-\lambda) > 0$, $h > 0$, in order to make $V_s(w_{HL,M}) \geq g_s(w_{HL,M}, LL)$, the following condition needs to be satisfied:

$$\delta(1+\delta)(1-h)(2\lambda-1) - 1 \geq 0 \tag{17}$$

The seller's average discounted value of taking a one-shot deviation to LH in the state $w_{HL,M}$ is:

$$g_s(w_{HL,M}, LH) = (1-\delta)[h\pi^l + (1-h)\pi^h] + \delta\big[h\lambda V_s(w_{HH,R}) + (1-h\lambda)V_s(w_{HL,M})\big] \tag{18}$$

$$\Rightarrow V_s(w_{HL,M}) - g_s(w_{HL,M}, LH)$$

$$= (1-\delta)[h(-\Delta\pi) + (1-h)\Delta\pi]$$

$$+ \delta\{[(1-h)(1-\lambda) - h\lambda]V_s(w_{HH,R})$$

$$+ [1-(1-h)(1-\lambda) - 1 + h\lambda]V_s(w_{HL,M})\}$$

$$= (1-\delta)(1-2h)\Delta\pi$$

$$+ \delta\{(1-h)(1-\lambda)V_s(w_{HH,R}) - h\lambda V_s(w_{HH,R}) + h\lambda V_s(w_{HL,M})$$

$$- (1-h)(1-\lambda)V_s(w_{HL,M})\}$$

$$= (1-\delta)(1-2h)\Delta\pi$$

$$+ \delta\left\{(1-h)(1-\lambda)\left(V_s(w_{HH,R} - w_{HL,M})\right) + h\lambda\left(V_s(w_{HL,M}) - V_s(w_{HH,R})\right)\right\}$$

$$= (1-\delta)(1-2h)\Delta\pi + \delta\left(V_s(w_{HH,R}) - V_s(w_{HL,M})\right)\left(h\lambda - (1-h)(1-\lambda)\right)$$

$$= (1-\delta)(1-2h)\Delta\pi + \frac{\delta(1-\delta^2)(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \cdot (h+\lambda-1)$$

$$= \Delta\pi(1-\delta)\left[(1-2h) + \frac{\delta(1+\delta)(1-h)(h+\lambda-1)}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right]$$

$$= \Delta\pi(1-\delta)$$

$$\cdot \frac{[\delta(1+\delta)(1-h)(h+\lambda-1) + (1-2h)[1+\delta(1+\delta)(1-h)(1-\lambda)]}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \Delta\pi(1-\delta)$$

$$\cdot \frac{\delta(1+\delta)(1-h)(h+\lambda-1) + 1 - 2h + (1-2h)\delta(1+\delta)(1-h)(1-\lambda)}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \Delta\pi(1-\delta) \cdot \frac{\delta(1+\delta)(1-h)\left(h+\lambda-1+(1-2h)(1-\lambda)\right) + 1 - 2h}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

$$= \Delta\pi(1-\delta) \cdot \frac{\delta(1+\delta)(1-h)h(2\lambda-1) + (1-2h)}{1+\delta(1+\delta)(1-h)(1-\lambda)}$$

(19)

Since $\Delta\pi(1-\delta) > 0$ and $1 + \delta(1+\delta)(1-h)(1-\lambda) > 0$, in order to make $V_s(w_{HL,M}) - g_s(w_{HL,M}, LH) \geq 0$, the following condition needs to be satisfied:

$$\delta(1+\delta)(1-h)h(2\lambda - 1) + (1-2h) \geq 0 \tag{20}$$

2.A.1.1.2. The buyer

The buyer's average discounted value in the $w_{HL,M}$ state in Period t is:

$$V_b^t(w_{HL,M}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(\lambda v - p^l)] + \delta\left[\psi_1^{t+1} V_b^{t+1}(w_{HL,M}) + \psi_2^{t+1} V_b^{t+1}(w_{HH,R}) + (1 - \psi_1^{t+1} - \psi_2^{t+1}) V_b^{t+1}(w'_{HH,R})\right] \tag{21}$$

where ψ_1^{t+1} (ψ_2^{t+1}) denotes the probability that the buyer's matched seller in Period $t+1$ is in the $w_{HL,M}$ ($w_{HH,R}$) state.[39]

Her average discounted value in the $w_{HH,R}$ state in Period t is:

$$V_b^t(w_{HH,R}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta\left[\psi_1^{t+1} V_b^{t+1}(w_{HL,M}) + \psi_2^{t+1} V_b^{t+1}(w_{HH,R}) + (1 - \psi_1^{t+1} - \psi_2^{t+1}) V_b^{t+1}(w'_{HH,R})\right] \tag{22}$$

Her average discounted value in the $w'_{HH,R}$ state in Period t is:

[39] $\psi_1^{t+1} = [1 \quad 0 \quad 0]\boldsymbol{M}^t \begin{bmatrix}1\\0\\0\end{bmatrix}$, $\psi_2^{t+1} = [1 \quad 0 \quad 0]\boldsymbol{M}^t \begin{bmatrix}0\\1\\0\end{bmatrix}$, where $\boldsymbol{M} = \begin{bmatrix}1-(1-h)(1-\lambda) & (1-h)(1-\lambda) & 0\\0 & 0 & 1\\1 & 0 & 0\end{bmatrix}$ is the state transition matrix.

$$
\begin{aligned}
V_b^t\left(w'_{HH,R}\right) &= (1-\delta)[h(\lambda v - p^h) + (1-h)(v-p^h)] \\
&\quad + \delta\left[\psi_1^{t+1}V_b^{t+1}\left(w_{HL,M}\right) + \psi_2^{t+1}V_b^{t+1}\left(w_{HH,R}\right) + (1-\psi_1^{t+1}-\psi_2^{t+1})V_b^{t+1}\left(w'_{HH,R}\right)\right] \\
&= V_b^t(w_{HH,R})
\end{aligned}
\tag{23}
$$

Her average discounted value in the $w''_{HH,R}$ state in Period t is:

$$
V_b^t\left(w''_{HH,R}\right) = h(\lambda v - p^h) + (1-h)(v-p^h) \tag{24}
$$

Her average discounted value of taking a one-shot deviation to R in the $w_{HL,M}$ state in Period t is:

$$
\begin{aligned}
g_b^t\left(w_{HL,M}, R\right) &= (1-\delta)\left[h(\lambda v - p^h) + (1-h)\left(\lambda v - p^l + (1-\lambda)(\beta-\gamma)\right)\right] \\
&\quad + \delta\left[(1-h)(1-\lambda)V_b^{t+1}\left(w''_{HH,R}\right)\right. \\
&\quad + \left(1-(1-h)(1-\lambda)\right)\left(\psi_1^{t+1}V_b^{t+1}\left(w_{HL,M}\right) + \psi_2^{t+1}V_b^{t+1}\left(w_{HH,R}\right)\right. \\
&\quad \left.\left. + (1-\psi_1^{t+1}-\psi_2^{t+1})V_b^{t+1}\left(w'_{HH,R}\right)\right)\right] \\
&= (1-\delta)\left[h(\lambda v - p^h) + (1-h)\left(\lambda v - p^l + (1-\lambda)(\beta-\gamma)\right)\right] \\
&\quad + \delta\left\{(1-h)(1-\lambda)[h(\lambda v - p^h) + (1-h)(v-p^h)]\right. \\
&\quad \left. + \left(1-(1-h)(1-\lambda)\right)\left(\psi_1^{t+1}V_b^{t+1}\left(w_{HL,M}\right) + (1-\psi_1^{t+1})V_b^{t+1}\left(w_{HH,R}\right)\right)\right\}
\end{aligned}
\tag{25}
$$

From (21) and (22), I know that:

$$
\begin{aligned}
V_b^t(w_{HL,M}) - V_b^t(w_{HH,R}) &= (1-\delta)(1-h)(\lambda v - p^l - v + p^h) \\
&= (1-\delta)(1-h)(p^h - p^l - (1-\lambda)v)
\end{aligned} \tag{26}
$$

From (21), (25) and (26), I know that:

$$
\begin{aligned}
&V_b^t(w_{HL,M}) - g_b^t(w_{HL,M}, R) \\
&\quad = -(1-\delta)(1-h)(1-\lambda)(\beta-\gamma) \\
&\quad + \delta\left\{\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\right. \\
&\quad - (1-h)(1-\lambda)[h(\lambda v - p^h) + (1-h)(v-p^h)] \\
&\quad \left. - \left(1-(1-h)(1-\lambda)\right)\left(\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b(w_{HH,R})\right)\right\} \\
&\quad = -(1-\delta)(1-h)(1-\lambda)(\beta-\gamma) \\
&\quad + \delta(1-h)(1-\lambda)\big[\psi_1^{t+1}V_b(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R}) - h(\lambda v - p^h) \\
&\quad - (1-h)(v-p^h)\big] \\
&\quad = -(1-\delta)(1-h)(1-\lambda)(\beta-\gamma) \\
&\quad + \delta(1-h)(1-\lambda)\big[\psi^{t+1}(1-\delta)(1-h)(p^h - p^l - (1-\lambda)v) + V_b^{t+1}(w_{HH,R}) \\
&\quad - h(\lambda v - p^h) - (1-h)(v-p^h)\big] \\
&\quad = -(1-\delta)(1-h)(1-\lambda)(\beta-\gamma) \\
&\quad + \delta(1-h)(1-\lambda)\big[\psi^{t+1}(1-\delta)(1-h)(p^h - p^l - (1-\lambda)v) + V_b^{t+1}(w_{HH,R}) \\
&\quad - \pi_{HH,R}\big]
\end{aligned} \tag{27}
$$

where $\pi_{HH,R} \equiv h(\lambda v - p^h) + (1-h)(v-p^h)$.

Define $\Delta\pi_{MR} \equiv V_b^t(w_{HL,M}) - V_b^t(w_{HH,R})$. With (26), the expression of $V_b^t(w_{HH,R})$ in (22) can be rewritten as:

$$V_b^t(w_{HH,R}) = (1-\delta)\pi_{HH,R} + \delta\left[\psi_1^{t+1}\left(V_b^{t+1}(w_{HH,R}) + \Delta\pi_{MR}\right) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\right]$$
$$= (1-\delta)\pi_{HH,R} + \delta V_b^{t+1}(w_{HH,R}) + \delta\psi_1^{t+1}\Delta\pi_{MR} \tag{28}$$

I iterate $V_b^{t+1}(w_{HH,R}), V_b^{t+2}(w_{HH,R}), \ldots, V_b^{t+n}(w_{HH,R})$ and so on, and then (28) can be written as:

$$V_b^t(w_{HH,R}) = (1-\delta)\pi_{HH,R} + \delta\left[(1-\delta)\pi_{HH,R} + \delta V_b^{t+2}(w_{HH,R}) + \delta\psi_1^{t+2}\Delta\pi_{MR}\right] + \delta\psi_1^{t+1}\Delta\pi_{MR}$$
$$= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R} + \delta^2 V_b^{t+2}(w_{HH,R}) + \delta^2\psi_1^{t+2}\Delta\pi_{MR}$$
$$+ \delta\psi_1^{t+1}\Delta\pi_{MR}$$
$$= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R}$$
$$+ \delta^2\left[(1-\delta)\pi_{HH,R} + \delta V_b^{t+3}(w_{HH,R}) + \delta\psi_1^{t+3}\Delta\pi_{MR}\right] + \delta^2\psi_1^{t+2}\Delta\pi_{MR}$$
$$+ \delta\psi_1^{t+1}\Delta\pi_{MR}$$
$$= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R} + \delta^2(1-\delta)\pi_{HH,R} + \delta^3 V_b^{t+3}(w_{HH,R})$$
$$+ \delta^3\psi_1^{t+3}\Delta\pi_{MR} + \delta^2\psi_1^{t+2}\Delta\pi_{MR} + \delta\psi_1^{t+1}\Delta\pi_{MR}$$
$$= (1-\delta)\pi_{HH,R}(\delta^0 + \delta^1 + \delta^2) + \delta^3 V_b^{t+3}(w_{HH,R})$$
$$+ \Delta\pi_{MR}(\delta\psi_1^{t+1} + \delta^2\psi_1^{t+2} + \delta^3\psi_1^{t+3})$$
$$= (1-\delta)\pi_{HH,R}(\delta^0 + \delta^1 + \delta^2 + \cdots + \delta^n) + \delta^{n+1} V_b^{t+n+1}(w_{HH,R})$$
$$+ \Delta\pi_{MR}(\delta\psi_1^{t+1} + \delta^2\psi_1^{t+2} + \cdots + \delta^{n+1}\psi_1^{t+n+1})$$

$$= (1-\delta)\pi_{HH,R} \cdot \lim_{k\to\infty}\sum_{l=0}^{k}\delta^{l} + \lim_{k\to\infty}\delta^{k+1} \cdot \lim_{k\to\infty} V_b^{t+k+1}(w_{HH,R}) + \Delta\pi_{MR} \cdot \lim_{k\to\infty}\sum_{l=0}^{k}\delta^{l+1}\psi_1^{t+l+1}$$

$$= (1-\delta)\pi_{HH,R} \cdot \frac{1}{1-\delta} + 0 + \Delta\pi_{MR} \cdot \lim_{k\to\infty}\sum_{l=0}^{k}\delta^{l+1}\psi_1^{t+l+1}$$

$$= \pi_{HH,R} + \Delta\pi_{MR} \cdot \sum_{l=0}^{\infty}\delta^{l+1}\psi_1^{t+l+1} > \pi_{HH,R} \tag{29}$$

Going back to (27), I can conclude that:

$$\lim_{\delta\to 1}\left(V_b^t(w_{HL,M}) - g_b^t(w_{HL,M}, R)\right) = (1-h)(1-\lambda)\left[V_b^{t+1}(w_{HH,R}) - \pi_{HH,R}\right] > 0 \tag{30}$$

In other words, when δ is sufficiently large, the buyer does not have the incentive to take a one-shot deviation to R in the $w_{HL,M}$ state (in any period).

2.A.1.2. The $w_{HH,R}$ state

2.A.1.2.1. The seller

The seller's average discounted value in the $w_{HH,R}$ state is:

$$V_s(w_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w'_{HH,R}) \tag{31}$$

Her average discounted values of taking a one-shot deviation to HL, LL and LH are:

$$g_s(w_{HH,R}, HL) = (1-\delta)[h\pi^h + (1-h)(\pi^l - (1-\lambda)\beta)] + \delta\left[(1-h)(1-\lambda)V_s(w''_{HH,R}) + \left(1-(1-h)(1-\lambda)\right)V_s(w'_{HH,R})\right] \tag{32}$$

$$g_s(w_{HH,R}, LL) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)(\pi^l - (1-\lambda)\beta)]$$
$$+ \delta\big[(1-(1-h)\lambda + (1-\lambda)h)V_s(w''_{HH,R}) + \big((1-h)\lambda + (1-\lambda)h\big)V_s(w'_{HH,R})\big] \tag{33}$$

$$g_s(w_{HH,R}, LH) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)\pi^h] + \delta\big[h\lambda V_s(w''_{HH,R}) + (1-h\lambda)V_s(w'_{HH,R})\big] \tag{34}$$

We can easily know that $V_s(w_{HH,R})$ is the highest among these four values, when (1) to (3) are satisfied. Thus, the seller does not have the incentive to deviate to any other behavior in the $w_{HH,R}$ state.

2.A.1.2.2. The buyer

In Section 2.A.1.2, I know that the buyer's average discounted value in the $w_{HH,R}$ state in Period t is:

$$\begin{aligned} V_b^t(w_{HH,R}) &= (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] \\ &+\delta\big[\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\big] \end{aligned} \tag{35}$$

Her average discounted values of taking a one-shot deviation to M is:

$$g_b^t(w_{HH,R}, M) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)]$$
$$+ \delta\big[\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\big] = V_b^t(w_{HH,R}) \tag{36}$$

Thus, the buyer does not have the incentive to deviate to M in the $w_{HH,R}$ state (in any period).

2.A.1.3. The $w'_{HH,R}$ state

2.A.1.3.1. The seller

We know that:

$$V_s(w_{HL,M}) = \pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \tag{37}$$

$$V_s(w''_{HH,R}) = \pi^h \tag{38}$$

Therefore:

$$V_s(w_{HL,M}) > V_s(w''_{HH,R}) \tag{39}$$

The seller's average discounted value in the $w'_{HH,R}$ state is:

$$V_s(w'_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w_{HL,M}) \tag{40}$$

Her average discounted values of taking a one-shot deviation to HL, LL and LH are:

$$\begin{aligned} g_s(w'_{HH,R}, HL) &= (1-\delta)[h\pi^h + (1-h)(\pi^l - (1-\lambda)\beta)] \\ &\quad + \delta\big[(1-h)(1-\lambda)V_s(w''_{HH,R}) + \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\big] \end{aligned} \tag{41}$$

$$\begin{aligned} g_s(w'_{HH,R}, LL) &= (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)(\pi^l - (1-\lambda)\beta)] \\ &\quad + \delta\big[(1-(1-h)\lambda + (1-\lambda)h)V_s(w''_{HH,R}) + \big((1-h)\lambda + (1-\lambda)h\big)V_s(w_{HL,M})\big] \end{aligned} \tag{42}$$

$$g_s\left(w'_{HH,R}, LH\right) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)\pi^h] + \delta\left[h\lambda V_s\left(w''_{HH,R}\right) + (1-h\lambda)V_s\left(w_{HL,M}\right)\right] \tag{43}$$

We can easily know that $V_s\left(w'_{HH,R}\right)$ is the highest among these four values, when (1) to (3) are satisfied. Thus, the seller does not have the incentive to deviate to any other behavior in the $w'_{HH,R}$ state.

2.A.1.3.2. The buyer

In Section 2.A.1.2, I know that the buyer's average discounted value in the $w_{HH,R}$ state in Period t is:

$$\begin{aligned} V_b^t\left(w'_{HH,R}\right) &= (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] \\ &+\delta\left[\psi_1^{t+1}V_b^{t+1}\left(w_{HL,M}\right) + (1-\psi_1^{t+1})V_b^{t+1}\left(w_{HH,R}\right)\right] \end{aligned} \tag{44}$$

Her average discounted values of taking a one-shot deviation to M is:

$$\begin{aligned} g_b^t\left(w'_{HH,R}, M\right) &= (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] \\ &+ \delta\left[\psi_1^{t+1}V_b^{t+1}\left(w_{HL,M}\right) + (1-\psi_1^{t+1})V_b^{t+1}\left(w_{HH,R}\right)\right] = V_b^t\left(w'_{HH,R}\right) \end{aligned} \tag{45}$$

Thus, the buyer does not have the incentive to deviate to M in the $w'_{HH,R}$ state (in any period).

2.A.1.4. The $w''_{HH,R}$ state

2.A.1.4.1. The seller

The seller's average discounted value in the $w''_{HH,R}$ state is:

$$V_s\left(w''_{HH,R}\right) = (1-\delta)\pi^h + \delta V_s\left(w''_{HH,R}\right) \tag{46}$$

Her average discounted values of taking a one-shot deviation to HL, LL and LH are:

$$g_s\left(w''_{HH,R}, HL\right) = (1-\delta)[h\pi^h + (1-h)(\pi^l - (1-\lambda)\beta)] + \delta V_s\left(w''_{HH,R}\right) \tag{47}$$

$$g_s\left(w''_{HH,R}, LL\right) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)(\pi^l - (1-\lambda)\beta)] + \delta V_s\left(w''_{HH,R}\right) \tag{48}$$

$$g_s\left(w''_{HH,R}, LH\right) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)\pi^h] + \delta V_s\left(w''_{HH,R}\right) \tag{49}$$

We can easily know that $V_s\left(w''_{HH,R}\right)$ is the highest among these four average values, when (1) to (3) are satisfied. Thus, the seller does not have the incentive to deviate to any other behavior in the $w''_{HH,R}$ state.

2.A.1.4.2. The buyer

The buyer's average discounted value in the $w''_{HH,R}$ state in Period t is:

$$V_b^t\left(w''_{HH,R}\right) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta V_b^t\left(w''_{HH,R}\right) \tag{50}$$

Her average discounted values of taking a one-shot deviation to M is:

$$g_b^t\left(w''_{HH,R}, M\right) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta V_b^t\left(w''_{HH,R}\right) = V_b^t\left(w''_{HH,R}\right) \tag{51}$$

Thus, the buyer does not have the incentive to deviate to M in the $w''_{HH,R}$ state (in any period).

I have proved that neither the seller nor the buyer has any incentive to take a one-shot deviation to any other behavior in each state, if (1) to (3) are satisfied, δ is sufficiently large and the following conditions are met:

$$\begin{cases} \delta(1+\delta)(1-h)(2\lambda-1)-1 \geq 0 \\ \delta(1+\delta)(1-h)h(2\lambda-1)+(1-2h) \geq 0 \end{cases}$$

■

2.A.2. Proposition 2: If all sellers and buyers follow the 2-period punishment hybrid strategy profile, then the probability that each seller and buyer is in the state $w_{q^h q^l, Calm}$ in Period t, ψ_t, converges to a constant as $t \to \infty$. Formally:

$$\lim_{t\to\infty} \psi_t = 1 - \left(\frac{y-1}{r\cos\theta - 1} - \frac{C_2 r \sin\theta}{r\cos\theta - 1}\right)$$

where:

$$r = \sqrt{S_1^2 + S_2^2 - \frac{y}{3}(S_1+S_2) - S_1 S_2 + \frac{y^2}{9}}$$

$$S_1 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27}+\frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}},\ S_2 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27}+\frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}}$$

$$x = (1-h)(1-\lambda),\ y = 1-(1-h)(1-\lambda),\ \theta = \arctan\frac{\frac{\sqrt{3}}{2}(S_1-S_2)}{\frac{y}{3}-\frac{1}{2}(S_1+S_2)} + \pi$$

$$C_2 = \frac{a}{b},\ a = \frac{y^2-1}{r^2\cos 2\theta} - \frac{y-1}{r\cos\theta - 1},\ b = \frac{r^2 \sin 2\theta}{r^2\cos 2\theta - 1} - \frac{r\sin\theta}{r\cos\theta}$$

Proof:

Denote the vector of each seller and buyer's probability of being in $w_{q^h q^l, Calm}$, $w_{q^h q^h, Cry}$ and $w'_{q^h q^h, Cry}$ states in Period t $(t = 0, 1, \ldots)$ as M_t. I have:

$$M_0 = [1 \quad 0 \quad 0]$$

$$M_1 = [y \quad x \quad 0]$$
$$M_2 = [y^2 \quad yx \quad x]$$
$$M_3 = [y^3 + x \quad y^2 x \quad yx]$$
$$\cdots$$
$$M_t = [1 \quad 0 \quad 0]\begin{pmatrix} y & x & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix}^t \tag{52}$$

where $x \equiv (1-h)(1-\lambda), y \equiv 1-(1-h)(1-\lambda)$.

Therefore, I can derive the recursive relation for ψ_t:

$$\psi_t = y\psi_{t-1} + x\psi_{t-3} \quad (t \geq 3) \tag{53}$$

To solve for the general term formula for ψ_n, I need to find all the roots of the following equation:

$$-k^3 + yk^2 + 0k + x = 0 \tag{54}$$

This equation has the following three roots:

$$k_1 = 1 \tag{55}$$

$$k_2 = \frac{y}{3} + \frac{-1+\sqrt{3}i}{2} \cdot \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} + \frac{-1-\sqrt{3}i}{2} \cdot \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} \tag{56}$$

$$k_3 = \frac{y}{3} + \frac{-1-\sqrt{3}i}{2} \cdot \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} + \frac{-1+\sqrt{3}i}{2} \cdot \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} \tag{57}$$

Then the general term formula for ψ_n should take the form of:

$$\psi_t = A + r^t(C_1 \cos t\theta + C_2 \sin t\theta) \tag{58}$$

where A, C_1 and C_2 are constants to be determined, and:

$$r = |k_2| = |k_3| = \sqrt{S_1^2 + S_2^2 - \frac{y}{3}(S_1 + S_2) - S_1 S_2 + \frac{y^2}{9}} \tag{59}$$

$$S_1 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}}, S_2 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} \tag{60}$$

$$\theta = \arctan \frac{\frac{\sqrt{3}}{2}(S_1 - S_2)}{\frac{y}{3} - \frac{1}{2}(S_1 + S_2)} + \pi \tag{61}$$

It can be verified that $r \in (0, 1)$ when $h \in (0, 1)$ and $\lambda \in (0.5, 1)$, so $r^t \to 0$ as $t \to \infty$. It is also obvious that $(C_1 \cos t\theta + C_2 \sin t\theta)$ is bounded. Therefore, we can conclude that $r^t(C_1 \cos t\theta + C_2 \sin t\theta) \to 0$ as $t \to \infty$. Therefore, I know that $\lim_{t\to\infty} \psi_t = A$.

To determine the values of A, I plug $\psi_0 = 1, \psi_1 = y, \psi_2 = y^2$ into the general term formula for ψ_t and solve the following system of equations:

$$\begin{cases} A + cos0 \cdot C_1 + sin0 \cdot C_2 = 1 \\ A + r\cos\theta \cdot C_1 + r\sin\theta \cdot C_2 = y \\ A + r^2\cos 2\theta \cdot C_1 + r^2\sin 2\theta = y^2 \end{cases} \tag{62}$$

I get:

$$\begin{cases} A = 1 - \left(\dfrac{y-1}{r\cos\theta - 1} - \dfrac{C_2 r\sin\theta}{r\cos\theta - 1}\right) \\ C_1 = \dfrac{y-1}{r\cos\theta - 1} - \dfrac{C_2 r\sin\theta}{r\cos\theta - 1} \\ C_2 = \dfrac{\dfrac{y^2-1}{r^2\cos 2\theta - 1} - \dfrac{y-1}{r\cos\theta - 1}}{\dfrac{r^2\sin 2\theta}{r^2\cos 2\theta - 1} - \dfrac{r\sin\theta}{r\cos\theta - 1}} \end{cases} \tag{63}$$

Therefore, I conclude that:

$$\lim_{t\to\infty} \psi_t = 1 - \left(\frac{y-1}{r\cos\theta - 1} - \frac{C_2 r\sin\theta}{r\cos\theta - 1}\right) \tag{64}$$

■

2.B. Additional Tables

Table 2.B.1.1: Reputation vs. Baseline in the late stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	-0.638	0.956	-0.0156	-2.553***	-0.006
	(1.034)	(1.040)	(3.401)	(0.948)	(0.056)
Constant	3.222***	-3.646***	-9.789**	5.114***	0.599***
	(0.937)	(0.990)	(4.792)	(0.979)	(0.047)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.1.2: Nudge vs. Baseline in the late stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-2.009	1.795	1.757	-1.185	0.003
	(1.502)	(1.627)	(1.827)	(1.053)	(0.063)
Constant	4.004***	-4.723***	-8.226***	6.680***	0.599***
	(1.250)	(1.538)	(2.035)	(2.274)	(0.047)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.1.3: Reputation+Nudge vs. Baseline in the late stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation+Nudge	-2.761**	2.600**	2.361	-0.756	0.109
	(1.230)	(1.192)	(2.939)	(0.942)	(0.070)
Constant	3.378***	-3.898***	-9.486***	5.654***	0.599***
	(0.967)	(1.020)	(2.794)	(1.198)	(0.047)
Observations	800	800	800	800	200

Notes:

1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.1.4: Reputation+Nudge vs. Reputation in the late stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-1.718*	1.283	2.361	1.689*	0.115*
	(0.951)	(0.931)	(2.939)	(0.980)	(0.061)
Constant	2.255***	-2.309***	-9.486***	2.319***	0.593***
	(0.664)	(0.654)	(2.794)	(0.803)	(0.030)
Observations	800	800	800	800	200

Notes:

1. The omitted reference condition is *Reputation*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.1.5: Reputation+Nudge vs. Nudge in the late stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	-1.024	1.070	0.502	0.320	0.106
	(1.133)	(1.111)	(1.659)	(1.009)	(0.068)
Constant	1.623*	-2.285***	-6.886***	4.459***	0.601***
	(0.849)	(0.840)	(1.391)	(1.068)	(0.043)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Nudge*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.2.1: Reputation vs. Baseline in the early stage (Random-effects regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	0.799	-0.475	-0.866	-1.819**	0.024
	(0.894)	(0.818)	(1.184)	(0.901)	(0.116)
Constant	0.00551	-0.451	-5.057***	4.436***	0.593***
	(0.673)	(0.619)	(0.923)	(0.854)	(0.071)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.2.2: Nudge vs. Baseline in the early stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-0.719	0.408	-1.339	-1.272	0.060
	(1.018)	(0.967)	(1.784)	(0.991)	(0.119)
Constant	-0.0249	-0.482	-5.880***	5.424***	0.593***
	(0.718)	(0.654)	(1.325)	(1.188)	(0.071)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.2.3: Reputation+Nudge vs. Baseline in the early stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation+Nudge	-0.309	0.114	0.856	-1.448	0.006
	(0.846)	(0.725)	(0.897)	(0.910)	(0.127)
Constant	0.00729	-0.438	-4.778***	5.494***	0.593***
	(0.670)	(0.597)	(0.757)	(1.104)	(0.071)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.2.4: Reputation+Nudge vs. Reputation in the early stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-0.997	0.512	1.804	0.447	-0.018
	(0.709)	(0.597)	(1.190)	(0.864)	(0.140)
Constant	0.702	-0.800*	-5.978***	2.471***	0.616***
	(0.527)	(0.480)	(1.100)	(0.599)	(0.092)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Reputation*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.2.5: Reputation+Nudge vs. Nudge in the early stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	0.355	-0.232	2.369	-0.254	-0.054
	(0.865)	(0.787)	(1.598)	(0.974)	(0.143)
Constant	-0.657	-0.106	-6.947***	3.695***	0.652***
	(0.687)	(0.654)	(1.357)	(0.746)	(0.096)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Nudge*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.3.1: Reputation vs. Baseline in the middle stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	-0.402	0.291	0.750	-1.828*	0.012
	(1.162)	(1.190)	(1.640)	(0.944)	(0.058)
Constant	2.620**	-2.863***	-7.837***	5.568***	0.551***
	(1.040)	(1.071)	(1.965)	(1.093)	(0.048)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.3.2: Nudge vs. Baseline in the middle stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-3.516	2.317	-0.0156	-1.234	0.082
	(3.390)	(2.596)	(3.401)	(0.995)	(0.063)
Constant	4.309*	-4.204**	-9.789**	5.523***	0.551***
	(2.227)	(1.964)	(4.792)	(1.217)	(0.048)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.3.3: Reputation+Nudge vs. Baseline in the middle stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation+Nudge	-2.416*	1.849	2.480	-0.972	0.119*
	(1.313)	(1.267)	(1.932)	(0.934)	(0.062)
Constant	2.659**	-2.896***	-8.469***	5.795***	0.551***
	(1.048)	(1.078)	(2.099)	(1.242)	(0.048)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Baseline*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.B.3.4: Reputation+Nudge vs. Reputation in the middle stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Nudge	-1.664	1.362	1.477	0.778	0.107**
	(1.029)	(1.051)	(1.453)	(0.983)	(0.051)
Constant	1.850**	-2.174***	-7.149***	3.288***	0.563***
	(0.749)	(0.818)	(1.537)	(0.895)	(0.033)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Reputation*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.B.3.5: Reputation+Nudge vs. Nudge in the middle stage (Random-effects logistic regressions)

VARIABLES	(1) $q^h q^h$	(2) $q^h q^l$	(3) $q^l q^l$	(4) Cry	(5) Efficiency
Reputation	-0.162	0.039	2.480	0.152	0.037
	(1.542)	(1.645)	(1.932)	(0.993)	(0.057)
Constant	0.433	-1.238	-8.469***	3.846***	0.633***
	(1.233)	(1.361)	(2.099)	(0.782)	(0.041)
Observations	800	800	800	800	200

Notes:
1. The omitted reference condition is *Nudge*.
2. Columns (1) to (4) are Random-effects Logistic regressions. Column (5) is a Random-effects linear regression.
3. Standard errors (in parentheses) are adjusted for clustering at the subject level in Columns (1) to (4) and at the session level in Column (5).
4. *** p<0.01, ** p<0.05, * p<0.1

Table 2.B.4.1: Correlation between crying behavior and the matched seller's historical proportion of q^h in *Baseline* and *Nudge* (Random-effects Logistic Regression, Periods 2-60)

VARIABLES	Cry
Matched seller's historical proportion of q^h	-0.347
	(0.263)
Constant	4.959***
	(0.856)
Observations	2,360

Notes:
1. Standard errors (in parentheses) are adjusted for clustering at the subject level.
2. *** p<0.01, ** p<0.05, * p<0.1

2.C. Procedures of Finding the Pareto-Efficient PPE

(Note: To simply notations, I use the following shortcuts for strategies: HL denotes q^hq^l; HH denotes q^hq^h; LL denotes q^lq^l; LH denotes q^lq^h; R denotes $Calm$; M denotes $Calm$. Therefore, $w_{q^hq^l,Calm}$ is denoted as $w_{HL,M}$; $w_{q^hq^h,Cry}$ is denoted as $w_{HH,R}$; $w'_{q^hq^h,Cry}$ is denoted as $w'_{HH,R}$; $w''_{q^hq^h,Cry}$ is denoted as $w''_{HH,R}$.)

The stage game Pareto-efficient strategy profile is (HL, M) (when (1) through (3) are satisfied), so the ideal outcome we want to achieve is that this strategy profile will be played as frequently as possible. In order for both sellers and buyers to stick to this strategy profile, each of them should play a behavior strategy that punishes deviating behaviors from the other side. When (HL, M) is played, the seller has the incentive to deviate to LL while the buyer has the incentive to deviate to R. Therefore, the seller should play a behavior strategy that punishes the buyer for playing R, while the buyer should play a behavior strategy that punishes the seller for playing LL.

A good candidate strategy to consider is the "grim-trigger" strategy. In a perfect monitoring Prisoner's Dilemma game, a "grim trigger strategy" player starts with playing *Cooperate* and permanently switch to *Defect* after seeing the other player playing *Defect*. An analogous "grim-trigger" strategy in this imperfect monitoring repeated game can be the following: (a) Both sellers and buyers first play the "cooperative" behavior (i.e., HL for sellers and M for buyers). (b) If the buyer observes that the public signal from the seller matched with her (hereafter, opponent seller) in the last period is LFR or LFM (i.e., the q^l treatment failed in the last period), or the public signal LFR or LFM has appeared in any of the previous periods from this seller, she plays R. Otherwise, she continues playing M. (c) After a period in which the public signal is LFR or LFM, the seller anticipates that the buyer will switch to R in the next period, so the seller switches permanently to HH in all the following periods. An automaton of this strategy profile is shown below (y_{s_i} denotes the public signal from the seller i's own pair):

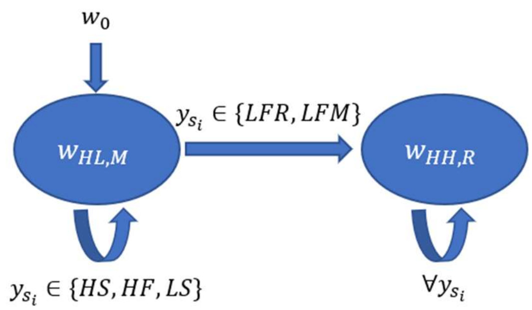


Figure 2.C.1. Automaton for the "grim-trigger" strategy profile

The state space is $W = \{w_{HL,M}, w_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$ and $f(w_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \\ w_{HH,R} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{LFR, LFM\}\right) \text{ or } \left(w = w_{HH,R} \text{ and } y_{s_i} \in \{HS, HF, LS, LFR, LFM\}\right) \end{cases} \tag{65}$$

Unfortunately, this "grim-trigger" strategy profile is not a PPE. The problem is that the buyer would have the incentive to have a one-shot deviation to R in the state $w_{HL,M}$. To demonstrate this problem formally, I write the buyer's average discounted value in the state $w_{HL,M}$ in Period t:

$$V_b^t(w_{HL,M}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(\lambda v - p^l)] + \delta\left[\psi^{t+1} V_b^{t+1}(w_{HL,M}) + (1-\psi^{t+1}) V_b^{t+1}(w_{HH,R})\right] \tag{66}$$

where ψ^{t+1} is the probability that her next opponent seller in Period $t+1$ is in the state $w_{HL,M}$, while $(1-\psi^{t+1})$ is the probability that her next opponent seller in Period $t+1$ is in the state $w_{HH,R}$.[40]

[40] $\psi^{t+1} = [1 \quad 0]\boldsymbol{M}^t \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, and where $\boldsymbol{M} = \begin{bmatrix} 1-(1-h)(1-\lambda) & (1-h)(1-\lambda) \\ 0 & 1 \end{bmatrix}$ is the state transition matrix.

If the buyer takes a one-shot deviation to R in Period t, her average discounted value in Period t will be:

$$g_b^t\left(w_{HL,M}, R\right) = (1-\delta)\left[h(\lambda v - p^h) + (1-h)\Big(\lambda v - p^l + (1-\lambda)(\beta-\gamma)\Big)\right] \\ +\delta\left[\psi^{t+1} V_b^{t+1}\left(w_{HL,M}\right) + (1-\psi^{t+1}) V_b^{t+1}\left(w_{HH,R}\right)\right] \qquad (67)$$

We can easily see that $g_b^t\left(w_{HL,M}, R\right) > V_b^t\left(w_{HL,M}\right)$, so I conclude that this "grim-trigger" strategy profile is not a PPE.

Another classic candidate strategy profile to consider is the "tit-for-tat" strategy. In a perfect monitoring Prisoner's Dilemma game, a "tit-for-tat" strategy player will start by playing *Cooperate* and then imitate the other player's behavior in the last period. An analogous "tit-for-tat" strategy in this repeated game can be the following: (a) Both sellers and buyers start with the cooperative behavior (i.e., HL for sellers and M for buyers). (b) If the buyer observes that the public signal of the opponent seller in the last period is LFM or LFR, then she plays R in the current period. If the public signal is HS, HF or LS, she plays M. (c) After a period in which the public signal is LFR or LFM, the seller anticipates that the buyer will switch to R in the next period, so the seller switches to HH in the next period and then switches back to HL in the period after next (because the public signal after choosing HH must be HS or HF). An automaton of this strategy profile is shown below:

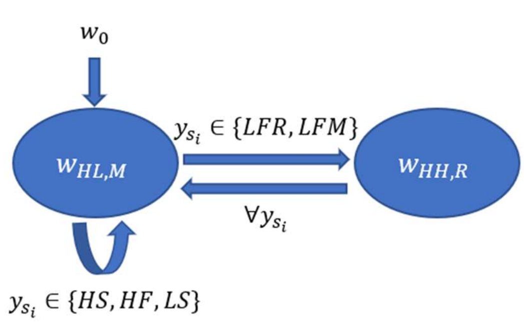


Figure 2.C.2. Automaton for the "tit-for-tat" strategy profile

The state space is $W = \{w_{HL,M}, w_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$ and $f(w_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w,y) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\}\right) \text{ or } \left(w = w_{HH,R} \text{ and } y_{s_i} \in \{HS, HF, LS, LFR, LFM\}\right) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{LFR, LFM\} \end{cases} \tag{68}$$

However, this strategy profile is not a PPE either, because the buyer still has the incentive to have a one-shot deviation to R in the state $w_{HL,M}$. We can see that the buyer's average discounted value in the state $w_{HL,M}$, $V_b^t(w_{HL,M})$, and her average discounted value of having a one-shot deviation to R in the state $w_{HL,M}$, $g_b(w_{HL,M}, R)$, are mostly the same as (65) and (66) respectively.[41]

From the analysis about the two strategy profiles above, we can see that the reason they fail to be PPEs is that the seller is unable to punish a buyer who deviates to R in the initial state. This is because the matching between the seller and buyer will be reshuffled after each period, so the seller herself is not *always* able to punish the same buyer in the next period. Considering this random matching feature, an effective punishment is that all sellers who observes a LFR signal from any seller-buyer pair (including her own pair) in the state $w_{HL,M}$ switches to HH in the next period, so that the buyer who takes the one-shot deviation will *always* be punished no matter which seller she is matched with in the next period. Therefore, the two strategy profiles above can be revised as follow (y_{s_j} denotes the public signal from *any* pair on the market, including the seller i's own pair):

[41] The only difference is that the state transition matrix for the "tit-for-tat" strategy profile is $\boldsymbol{M} = \begin{bmatrix} 1-(1-h)(1-\lambda) & (1-h)(1-\lambda) \\ 1 & 0 \end{bmatrix}$. This does not affect the conclusion that $g_b^t(w_{HL,M}, R) > V_b^t(w_{HL,M})$.

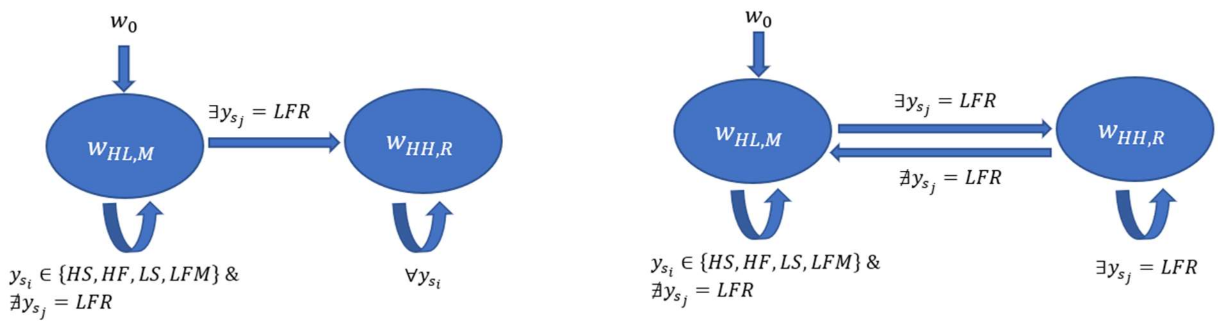


Figure 2.C.3. Revised "grim-trigger" and "tit-for-tat" strategy profiles

Formally, the revised "grim-trigger" strategy profile can be described as follow. The state space is $W = \{w_{HL,M}, w_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$ and $f(w_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w,a) = \begin{cases} w_{HL,M} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS, LFM\} \text{ and } \nexists y_{s_j} = LFR \\ w_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w_{HH,R} \end{cases} \tag{69}$$

The revised "tit-for-tat" strategy profile can be described as follow. The state space is $W = \{w_{HL,M}, w_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$ and $f(w_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w,a) = \begin{cases} w_{HL,M} & \begin{array}{c} \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS, LFM\} \text{ and } \nexists y_{s_j} = LFR\right) \\ \text{or } \left(w = w_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \end{array} \\ w_{HH,R} & \text{if } \exists y_{s_j} = LFR \end{cases} \tag{70}$$

However, these two revised strategy profiles are still not PPEs. The problem this time is that the seller would have the incentive to have a one-shot deviation to LL. For both strategy profiles, the seller's average discounted value in the state $w_{HL,M}$ is:

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta V_s(w_{HL,M}) \quad (71)$$

where $\pi^h \equiv p^h - c^h$ and $\pi^l \equiv p^l - c^l$.

The seller's average discounted value of having a one-shot deviation to LL in the state $w_{HL,M}$ (for both strategy profiles) is:

$$g_s(w_{HL,M}, LL) = (1-\delta)\pi^l + \delta V_s(w_{HL,M}) \quad (72)$$

With (2), we can easily see that $g_s(w_{HL,M}, LL) > V_s(w_{HL,M})$.

Now I summarize what I have learned from the failure of the four strategy profiles above. From the seller's perspective, to eliminate the buyer's incentive to deviate to R in the state $w_{HL,M}$, the seller should react with HH when observing a signal LFR (from any seller-buyer pair). On the other hand, the buyer who is willing to play M in the state $w_{HL,M}$ should switch to R in the next period in order to eliminate the seller's incentive to play LL in the state $w_{HL,M}$. Anticipating this reaction by the buyer, the seller should also switch to HH in the next period when observing a signal LFM. In other words, no matter whether the public signal in the previous period is LFR or LFM, the seller and buyer must enter a state where the strategy profile (HH, R) is played. However, the failure of the original "grim-trigger" and "tit-for-tat" strategies suggests that this state cannot be the same one for both LFR and LFM signals (because it would make it profitable for the buyer to make a one-shot deviation to R in the state $w_{HL,M}$). The only solution is to make the buyer enter a worse-off *subsequent* state if the buyer deviates to R in the state $w_{HL,M}$.

A good way to create two different subsequent states is to use a "grim-trigger" strategy profile after a LFR signal from any pair and use a "tit-for-tat" strategy profile if the signal is LFM. In this way, a buyer who deviates to R in the state $w_{HL,M}$ will be seriously punished because she will be punished by all sellers' HH strategy forever, while a buyer who sticks to M is still able to punish a seller who deviates to LL in the state $w_{HL,M}$ (because this seller will receive a lower payoff in the next period when the buyer switches to R) and, at the same time, still leave open the possibility of returning to the state $w_{HL,M}$. The automaton below describes this hybrid strategy profile:

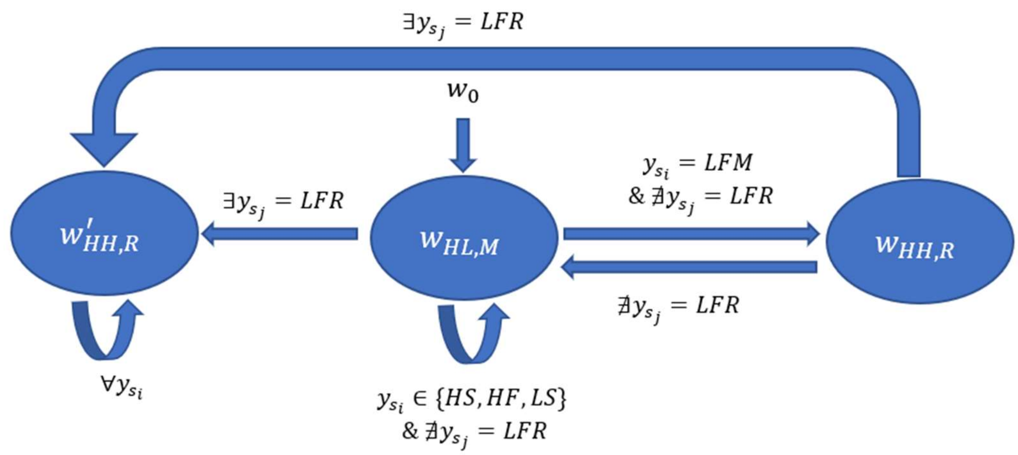


Figure 2.C.4. A 1-period punishment hybrid strategy profile

The state space is $W = \{w_{HL,M}, w_{HH,R}, w'_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$, $f(w_{HH,R}) = (HH, R)$ and $f(w'_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \text{ and } \nexists y_{s_j} = LFR\right) \\ & \text{or } \left(w = w_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} = LFM \text{ and } \nexists y_{s_j} = LFR \\ w'_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w'_{HH,R} \end{cases} \tag{73}$$

Unfortunately, this hybrid strategy profile fails to be a PPE again, and the problem is that the seller still has the incentive to take a one-shot deviation to LL in the state $w_{HL,M}$.

Proposition C.1: When (1) to (4) are satisfied, for $\forall\delta \in (0,1), \forall h \in (0,1), \forall\lambda \in (0.5,1)$, the hybrid strategy profile described by the automaton in Figure 2.C.4 is not a PPE.

Proof: The seller's average discounted value in the state $w_{HL,M}$ and $w_{HH,R}$ are:

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta\big[(1-h)(1-\lambda)V_s(w_{HH,R}) + \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\big] \tag{74}$$

$$V_s(w_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w_{HL,M}) \tag{75}$$

Plugging (75) into (74), I have:

$$\begin{aligned}
V_s(w_{HL,M}) &= (1-\delta)[h\pi^h + (1-h)\pi^l] \\
&\quad + \delta\Big[(1-h)(1-\lambda)\Big((1-\delta)\pi^h + \delta V_s(w_{HL,M})\Big) \\
&\quad + \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\Big] \\
&= (1-\delta)[h\pi^h + (1-h)\pi^l] \\
&\quad + \delta\big[(1-h)(1-\lambda)(1-\delta)\pi^h + \big(1-(1-h)(1-\lambda)(1-\delta)\big)V_s(w_{HL,M})\big] \\
&= (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta(1-h)(1-\lambda)(1-\delta)\pi^h \\
&\quad + \delta\big(1-(1-h)(1-\lambda)(1-\delta)\big)V_s(w_{HL,M})
\end{aligned}$$

$$\begin{aligned}
&\Rightarrow \big[1-\delta\big(1-(1-h)(1-\lambda)(1-\delta)\big)\big]V_s(w_{HL,M}) \\
&\qquad = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta(1-h)(1-\lambda)(1-\delta)\pi^h \\
&\Rightarrow (1-\delta)[1+\delta(1-h)(1-\lambda)]V_s(w_{HL,M}) \\
&\qquad = (1-\delta)[h\pi^h + (1-h)\pi^l + \delta(1-h)(1-\lambda)\pi^h] \\
&\Rightarrow V_s(w_{HL,M}) = \frac{h\pi^h + (1-h)\pi^l + \delta(1-h)(1-\lambda)\pi^h + \pi^h - \pi^h}{1+\delta(1-h)(1-\lambda)} \\
&\qquad = \pi^h + \frac{(1-h)\pi^h - (1-h)\pi^l}{1+\delta(1-h)(1-\lambda)} = \pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}
\end{aligned} \tag{76}$$

Plugging (62) into (61), I have:

$$V_s(w_{HH,R}) = \pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)} \tag{77}$$

The seller's average discounted value of having a one-shot deviation to LL in the state $w_{HL,M}$ is:

$$g_s(w_{HL,M}, LL) = (1-\delta)\pi^l$$
$$+\delta\left[(1-(1-h)\lambda-(1-\lambda)h)V_s(w_{HH,R}) + ((1-h)\lambda+(1-\lambda)h)V_s(w_{HL,M})\right] \tag{78}$$

Now I can compare $V_s(w_{HL,M})$ and $g_s(w_{HL,M}, LL)$:

$$V_s(w_{HL,M}) - g_s(w_{HL,M}, LL)$$
$$= (1-\delta)[h\pi^h + (1-h)\pi^l - \pi^l]$$
$$+ \delta\big[V_s(w_{HH,R})\big((1-h)(1-\lambda) - (1-(1-h)\lambda-(1-\lambda)h)\big)$$
$$+ V_s(w_{HL,M})(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)\big]$$
$$= (1-\delta)(-h\Delta\pi)$$
$$+ \delta\left[\left(\pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right)\big((1-h)(1-\lambda)+(1-h)\lambda+(1-\lambda)h-1\big)\right.$$
$$\left. + \left(\pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right)(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)\right]$$
$$= (1-\delta)(-h\Delta\pi)$$
$$+ \delta\left[(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h) \cdot \frac{(1-\delta)(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right]$$

$$= (1-\delta)\Delta\pi \left[\frac{\delta(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)(1-h)}{1+\delta(1-h)(1-\lambda)} - h\right]$$

$$= (1-\delta)\Delta\pi \left[\frac{\delta(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h](1-h)}{1+\delta(1-h)(1-\lambda)}\right.$$

$$\left. - \frac{h+h\delta(1-h)(1-\lambda)}{1+\delta(1-h)(1-\lambda)}\right]$$

$$= (1-\delta)\Delta\pi$$

$$\cdot \frac{\delta\big(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h-h(1-\lambda)\big)(1-h)-h}{1+\delta(1-h)(1-\lambda)}$$

$$= (1-\delta)\Delta\pi \cdot \frac{\delta h(1-h)(2\lambda-1)-h}{1+\delta(1-h)(1-\lambda)} = (1-\delta)\Delta\pi \cdot \frac{h[\delta(1-h)(2\lambda-1)-1]}{1+\delta(1-h)(1-\lambda)} \tag{79}$$

$$\left.\begin{array}{r} \lambda \in (0.5,1) \Rightarrow 2\lambda-1 \in (0,1) \\ \delta \in (0,1) \\ h \in (0,1) \end{array}\right\} \Rightarrow \delta(1-h)(2\lambda-1)-1 < 0 \tag{80}$$

From (79) and (80), I know that $V_s(w_{HL,M}) - g_s(w_{HL,M}, LL) < 0$. The seller has the incentive to have a one-shot deviation to LL in the state $w_{HL,M}$. Therefore, the hybrid strategy profile is not a PPE.

■

Proposition C.1 suggests that the buyer's punishment for the seller's taking a one-shot deviation to LL in the state $w_{HL,M}$ is not strong enough. A simple way for the buyer to strengthen the punishment is to play R for the next *two* periods instead of only one, after a LFM signal is observed from any pair. Anticipating this two-period punishment, the seller will also play HH for the next periods. The hybrid strategy profile can be revised as follow:

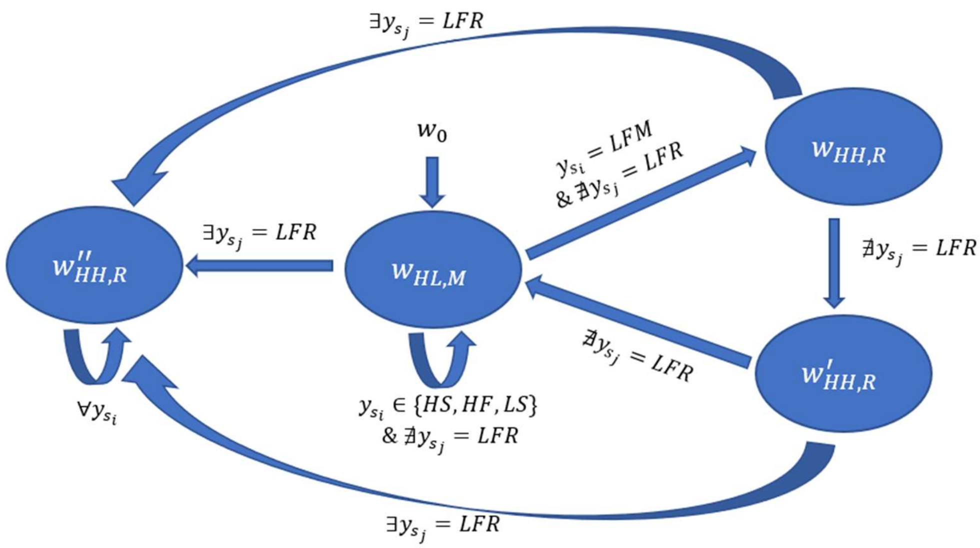


Figure 2.C.5. A 2-period punishment hybrid strategy profile

The state space is $W = \{w_{HL,M}, w_{HH,R}, w'_{HH,R}, w''_{HH,R}\}$. The initial state is $w_{HL,M}$. The output functions are $f(w_{HL,M}) = (HL, M)$, $f(w_{HH,R}) = (HH, R)$, $f(w'_{HH,R}) = (HH, R)$ and $f(w''_{HH,R}) = (HH, R)$. The transition function is:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \text{ and } \nexists y_{s_j} = LFR\right) \\ & \text{or } \left(w = w'_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} = LFM \text{ and } \nexists y_{s_j} = LFR \\ w'_{HH,R} & \text{if } w = w'_{HH,R} \text{ and } \nexists y_{s_j} = LFR \\ w''_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w''_{HH,R} \end{cases} \tag{81}$$

In Proposition 2, I prove that this 2-period punishment hybrid strategy profile is a PPE if some conditions are met.

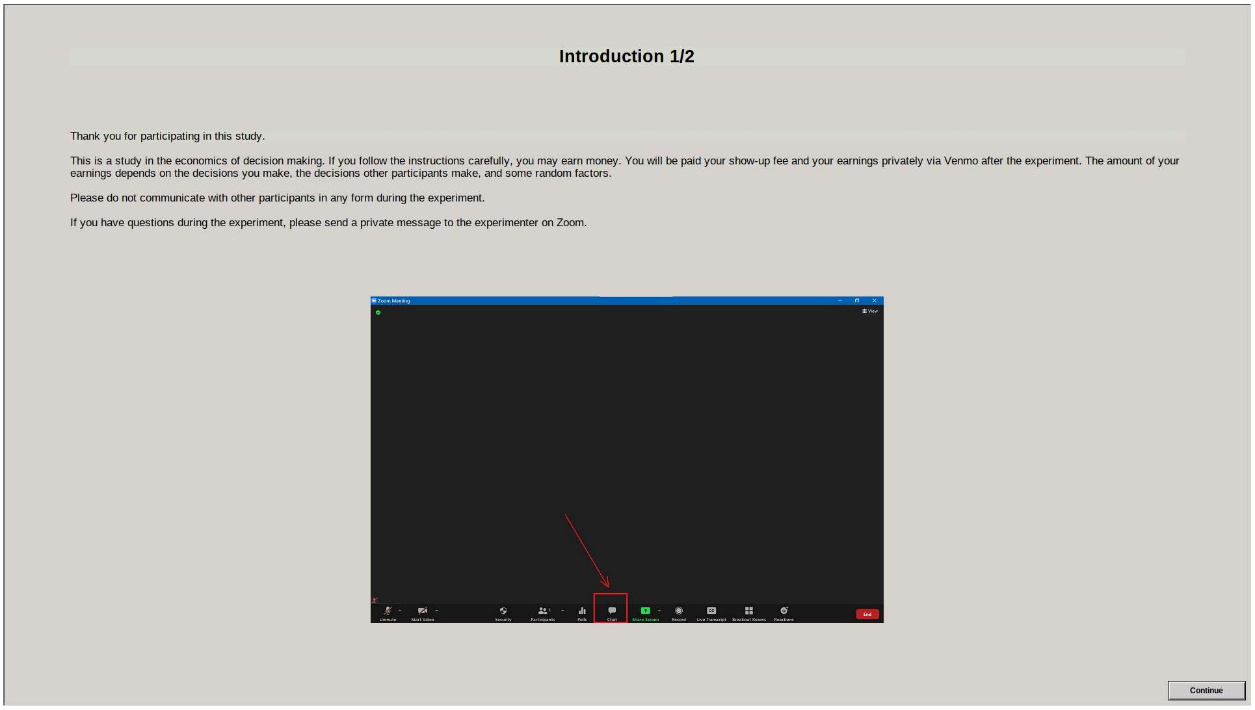
Proposition 2: The 2-period punishment hybrid strategy profile described by the automaton in Figure 2.C.5 is a PPE, if (1) to (3) are satisfied, δ is sufficiently large and the following additional conditions are met:

$$\begin{cases} \delta(1+\delta)(1-h)(2\lambda-1)-1 \geq 0 \\ \delta(1+\delta)(1-h)h(2\lambda-1)+(1-2h) \geq 0 \end{cases}$$

Proof: See Appendix 2.A.

Therefore, we find a PPE other than the stage-game perfect Bayesian equilibrium when the reputation system is introduced. Since the Pareto-efficient state $w_{HL,M}$ is frequently reached in this PPE, this PPE must increase the total expected payoffs of both sellers and buyers.

2.D. Experimental Instructions



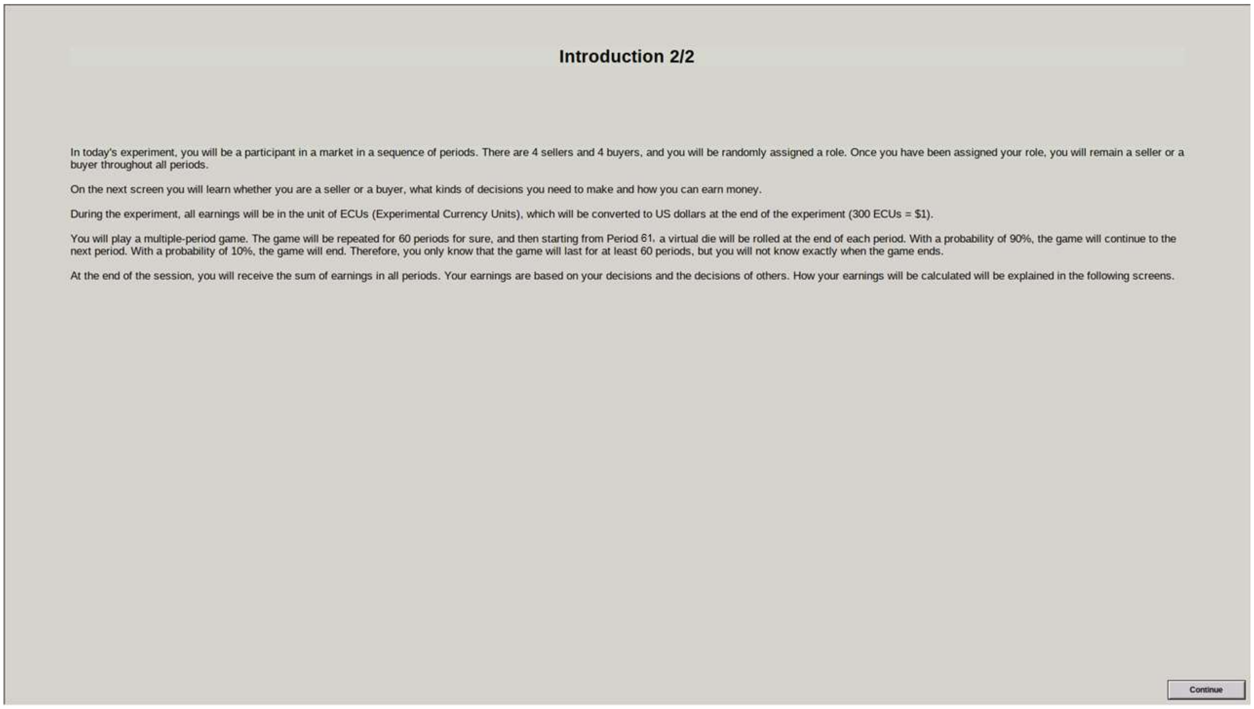


Figure 2.D.1. Experimental Instructions Screens 1-2

Your role in the experiment

You are a buyer for all periods today.

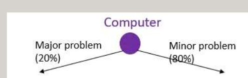
Continue

Buyer has a problem to be solved

At the beginning of each period, the computer will randomly match one seller with one buyer, and this matching will be reshuffled after each period (in other words, you will be most likely paired with a different seller/buyer in each period).

In each period, the buyer will encounter a problem that needs to be solved. The problem is either a **major** problem or a **minor** problem. There is a 20% chance that the problem is a **major** one and a 80% chance that it is a **minor** one.

The buyer him/herself is NOT able to identify the type of his/her problem. Only the seller can identify whether the buyer's problem is a **major** one or a **minor** one.



Continue

Figure 2.D.2. Experimental Instructions Screens 3-4

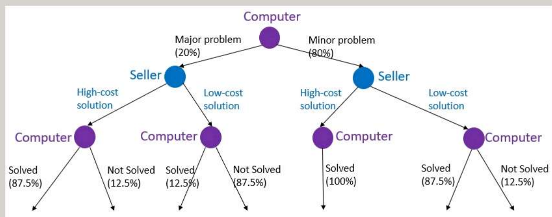
Seller chooses a solution to the buyer's problem 3/3

After identifying the buyer's problem, the seller can choose either a **high-cost** solution or a **low-cost** solution.

• If the buyer's problem is a **major** one, then:
  - A **high-cost** solution solves the buyer's **major** problem with a probability of 87.5% and fails to solve the problem with a probability of 12.5%.
  - A **low-cost** solution solves the buyer's **major** problem with a probability of 12.5% and fails to solve the problem with a probability of 87.5%.

• If the buyer's problem is a **minor** one, then:
  - A **high-cost** solution solves the buyer's **minor** problem with a probability of 100%.
  - A **low-cost** solution solves the buyer's **minor** problem with a probability of 87.5% and fails to solve the problem with a probability of 12.5%.

The graph below describes the procedures so far:



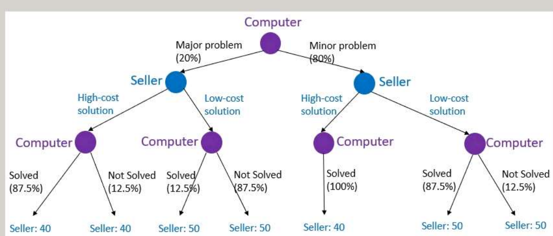
Continue

The seller's potential profit 3/3

The seller can now figure out his/her **potential profit.** After the seller chooses a solution to the buyer's problem, the seller pays a cost for the solution and charges the buyer a price.

• If the seller chooses a **high-cost** solution, he/she pays a cost of 40 ECUs and charges the buyer a price of 80 ECUs. Therefore, the seller's **potential profit** for choosing a **high-cost** solution is 80 - 40 = 40 ECUs.
• If the seller chooses a **low-cost** solution, he/she pays a cost of 0 ECUs and charges the buyer a price of 50 ECUs. Therefore, the seller's **potential profit** for choosing a **low-cost** solution is 50 - 0 = 50 ECUs.

The graph below demonstrates the steps described so far and the seller's potential profit in each scenario:



Continue

Figure 2.D.3. Experimental Instructions Screens 5-6

The buyer's potential profit 6/6

The buyer's **potential profit** in each period equals to the **revenue** he/she receives from the seller solution minus the price the seller charges her for the solution.

The **revenue** is determined by whether his/her problem is solved.

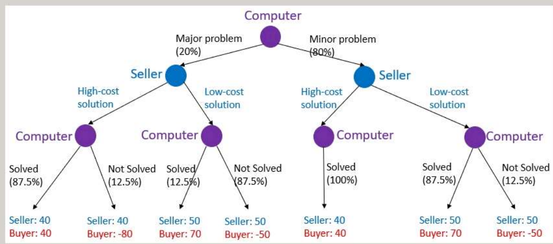
• If the buyer's problem is solved, then he/she receives a **revenue** of 120 ECUs.
• If the buyer's problem is NOT solved, then he/she receives a **revenue** of 0 ECUs.

As stated in the last screen, when the seller chooses a **high-cost** solution, the **price** the seller charges the buyer is 80 ECUs. When the seller chooses a **low-cost** solution, the **price** the seller charges the buyer is 50 ECUs.

Therefore, the buyer's **potential profit** in different situations can be summarized as below:

• If the seller chooses a **high-cost** solution, and the buyer's problem is **solved,** then the buyer's **potential profit** is 120 - 80 = 40 ECUs.
• If the seller chooses a **high-cost** solution, and the buyer's problem is **NOT solved,** then the buyer's **potential profit** is 0 - 80 = -80 ECUs.
• If the seller chooses a **low-cost** solution, and the buyer's problem is **solved,** then the buyer's **potential profit** is 120 - 50 = 70 ECUs.
• If the seller chooses a **low-cost** solution, and the buyer's problem is **NOT solved** , then the buyer's **potential profit** is 0 - 50 = -50 ECUs.

The graph below demonstrates the steps described so far and the potential profit of the seller and buyer in each scenario.



Continue

One more decision that determines the seller's and the buyer's FINAL profit 6/6

In each period, if the seller chooses a **low-cost** solution and the problem is **NOT solved,** the buyer can make one more decision. The buyer can choose from the following two options:

• **Demand:** "The seller should compensate me!"
• **Not Demand:** "I do not ask the seller to compensate me."

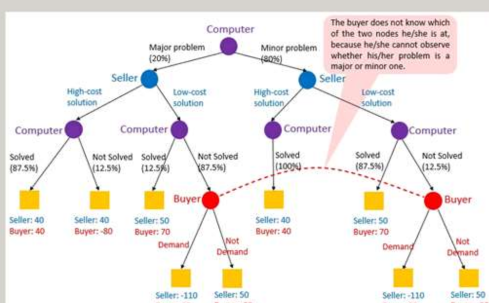
If the buyer chooses **Demand,** then the buyer first pays 20 ECUs to make the demand and then the seller must transfer 160 ECUs to the buyer. In other words, the buyer's **final profit** in this period = the buyer's **potential profit** - 20 ECUs + 160 ECUs = 90 ECUs, while the seller's **final profit** in this period = the seller's **potential profit** - 160 ECUs = -110 ECUs.

If the buyer chooses **Not Demand,** then there will be no transfer of ECUs between the buyer and the seller. Both the seller's and the buyer's **final profits** are equal to their **potential profits.**

If the seller chooses a **high-cost** solution in this period, no matter whether the problem is solved or not, the buyer is NOT able to make the abovementioned decision, and the seller's and the buyer's final profits are equal to their **potential profits.**

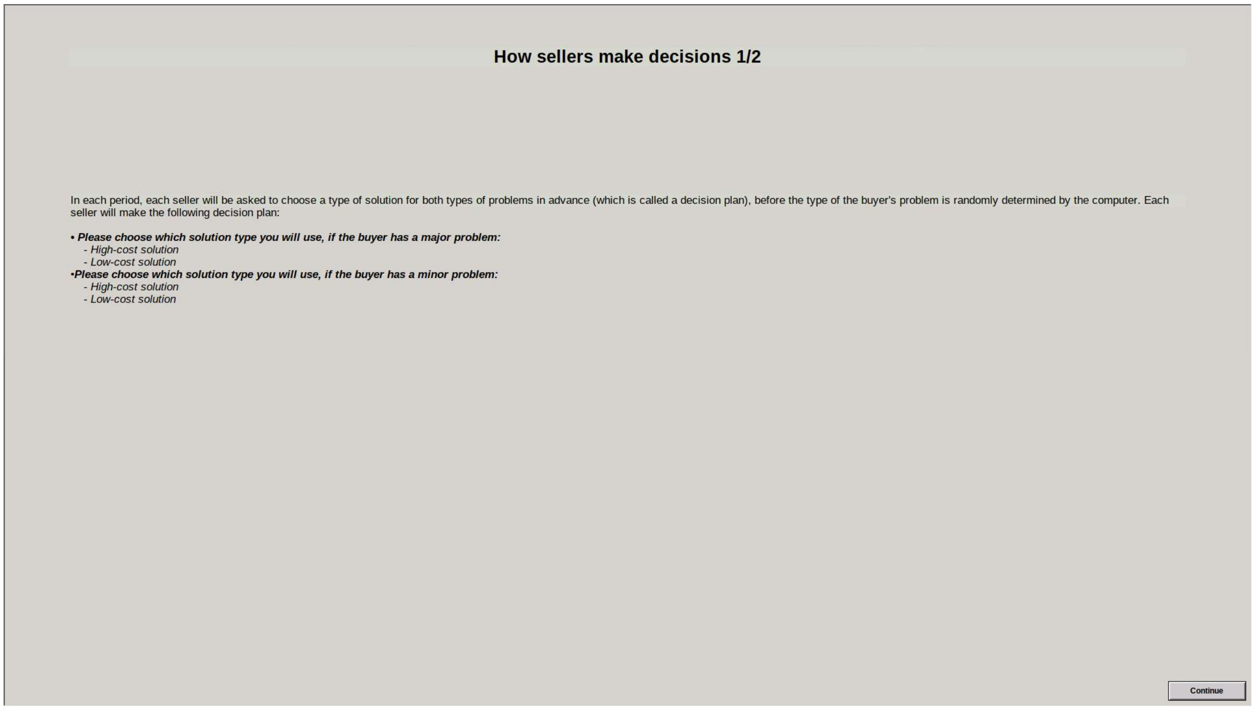
If the seller chooses a **low-cost** solution in this period and the problem is solved, the buyer is NOT able to make the abovementioned decision either, and the seller's and the buyer's **final profits** are equal to their **potential profits.**

The graph below describes the entire procedures and the final profits of the seller and buyer in each period:



Continue

Figure 2.D.4. Experimental Instructions Screens 7-8



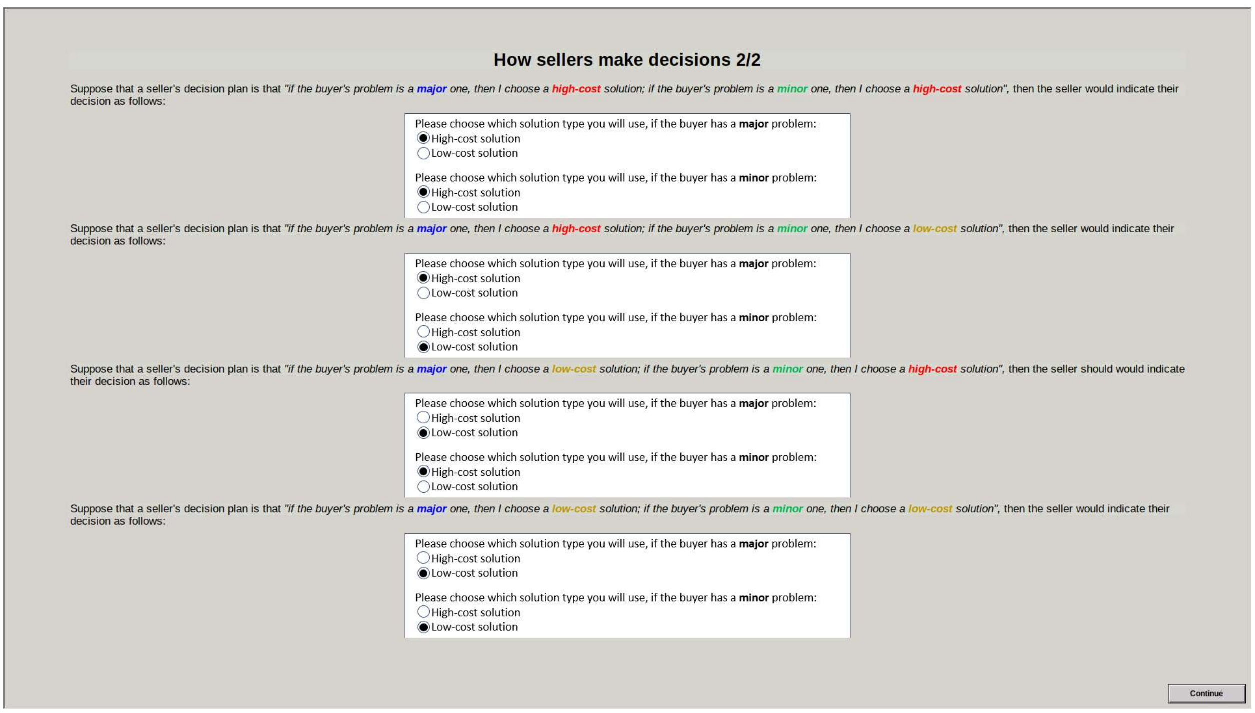
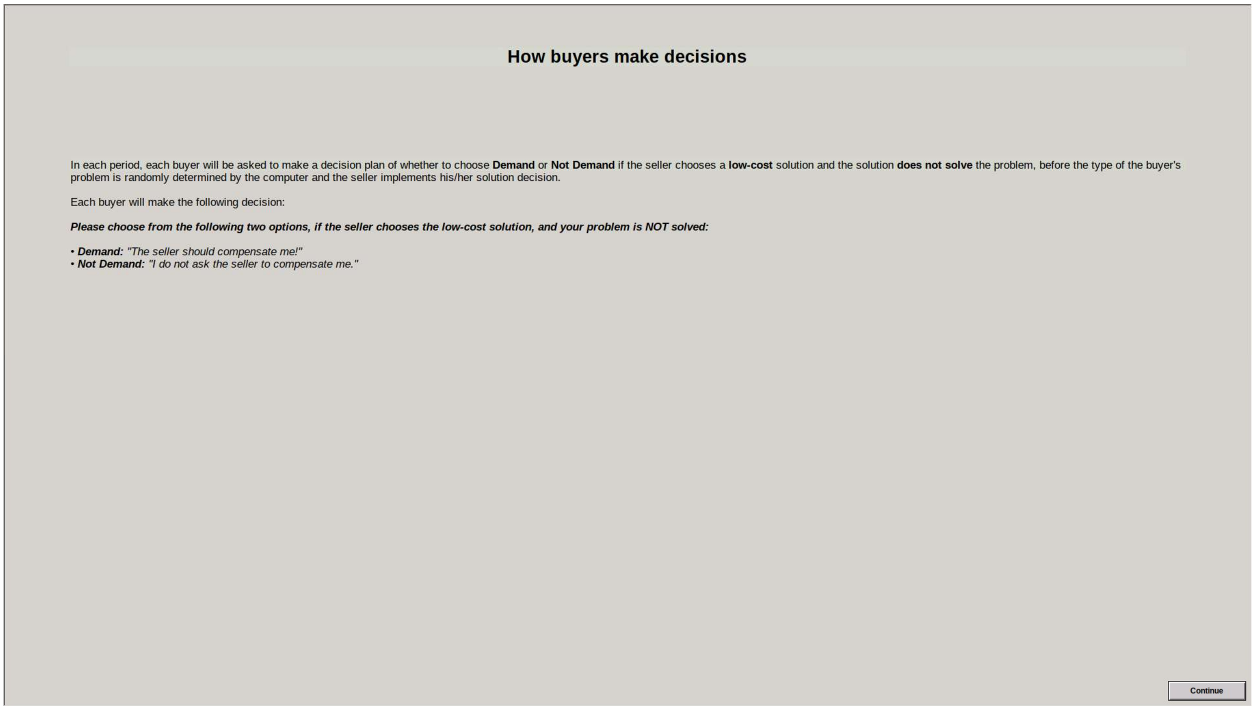


Figure 2.D.5. Experimental Instructions Screens 9-10



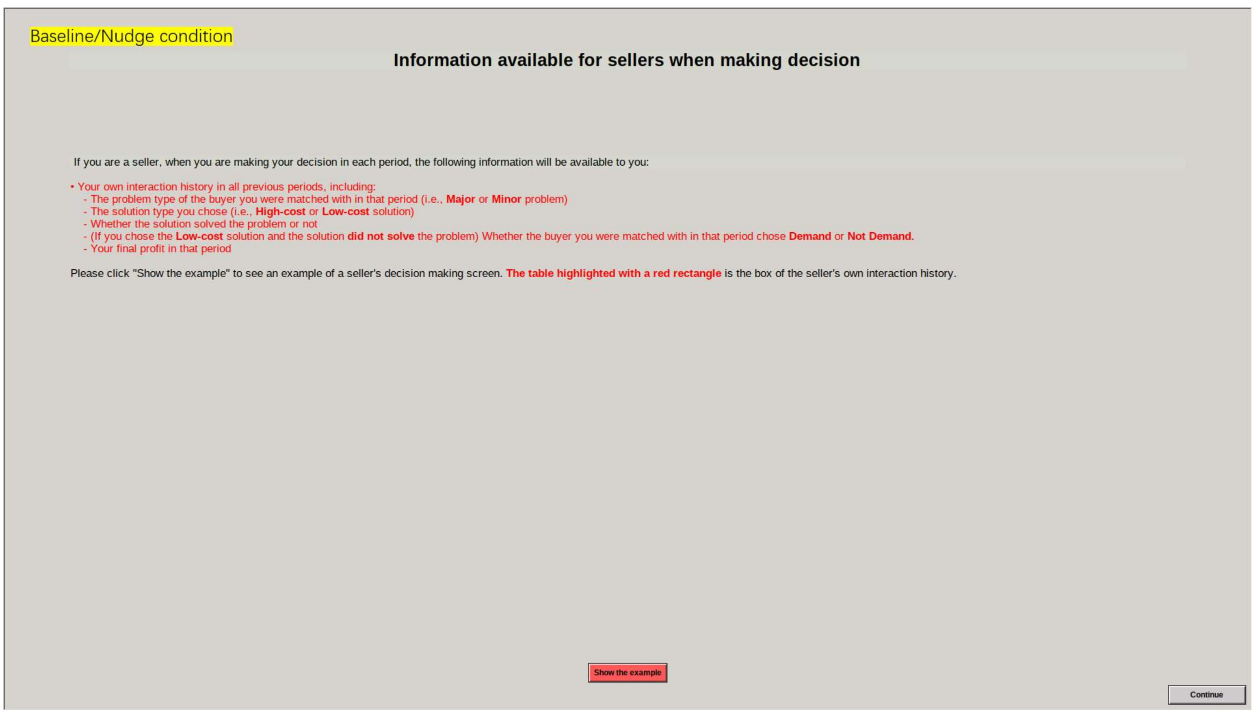
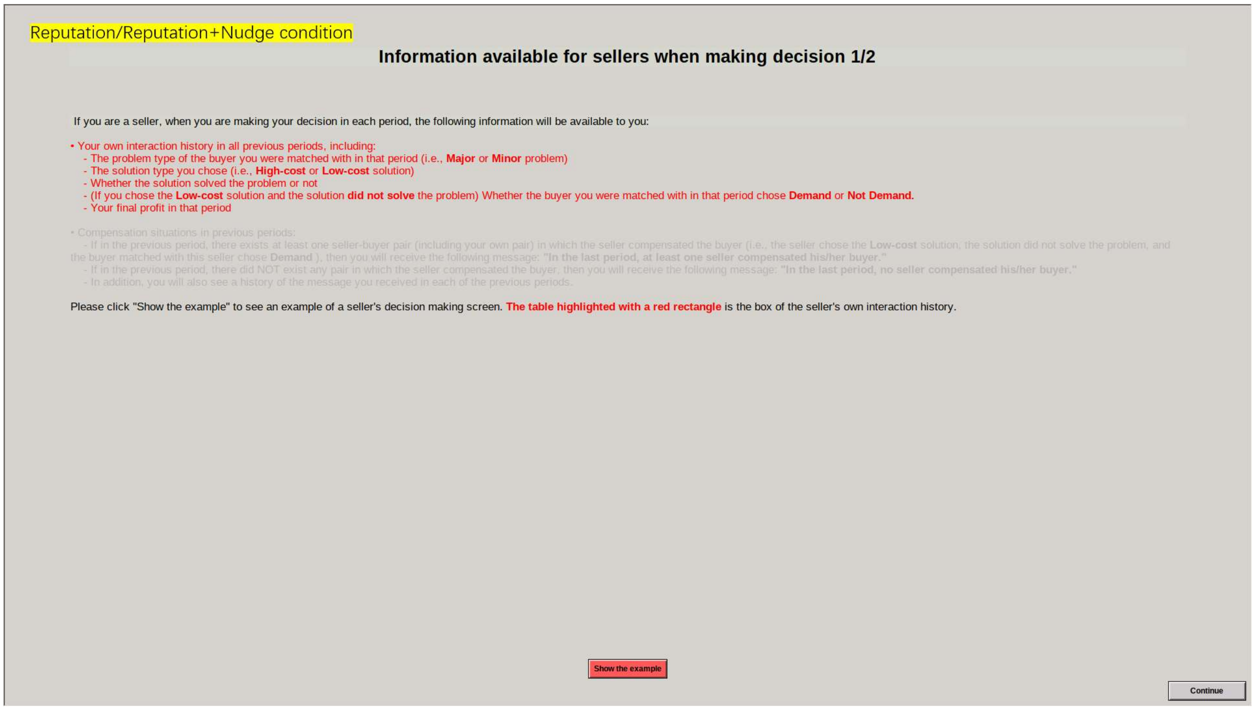


Figure 2.D.6. Experimental Instructions Screens 11-12



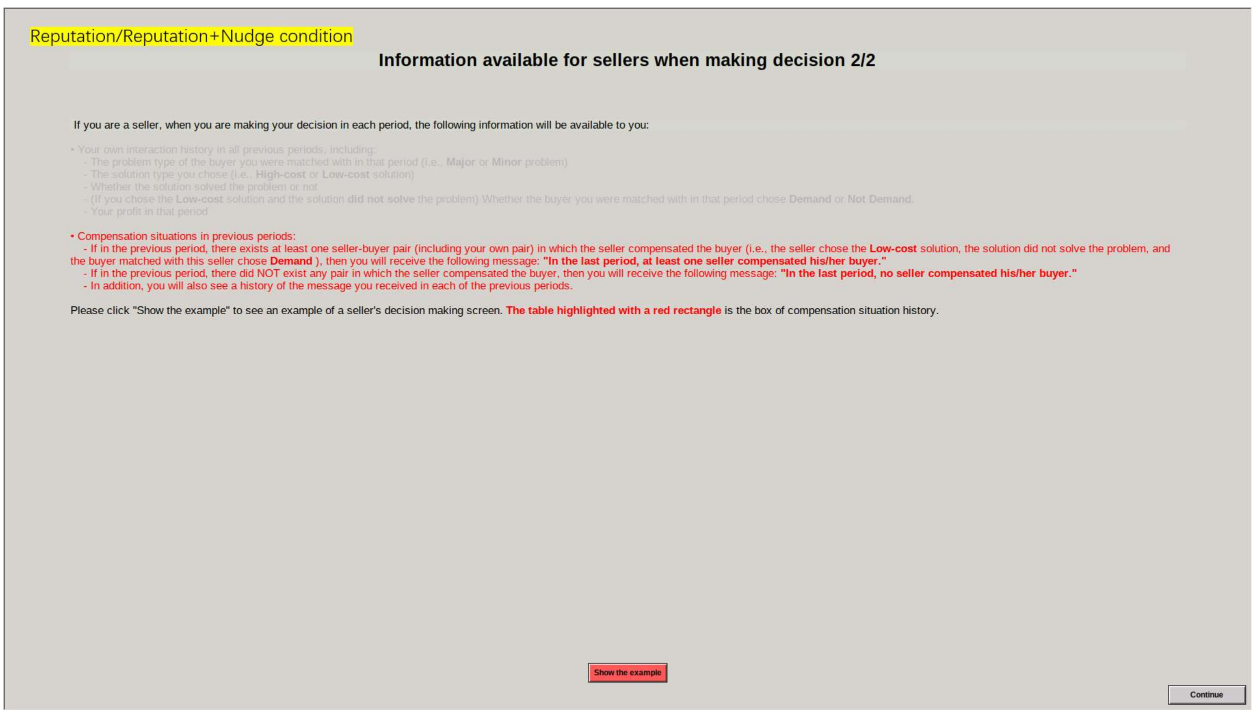
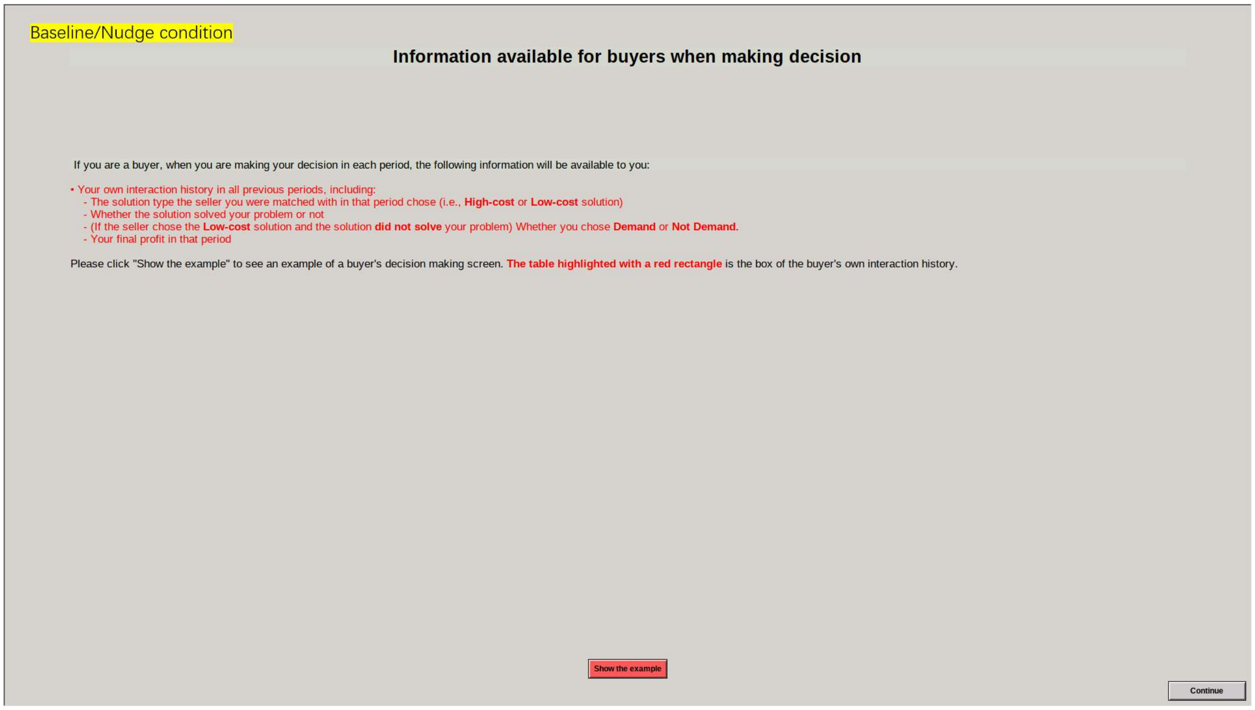


Figure 2.D.7. Experimental Instructions Screens 13-14



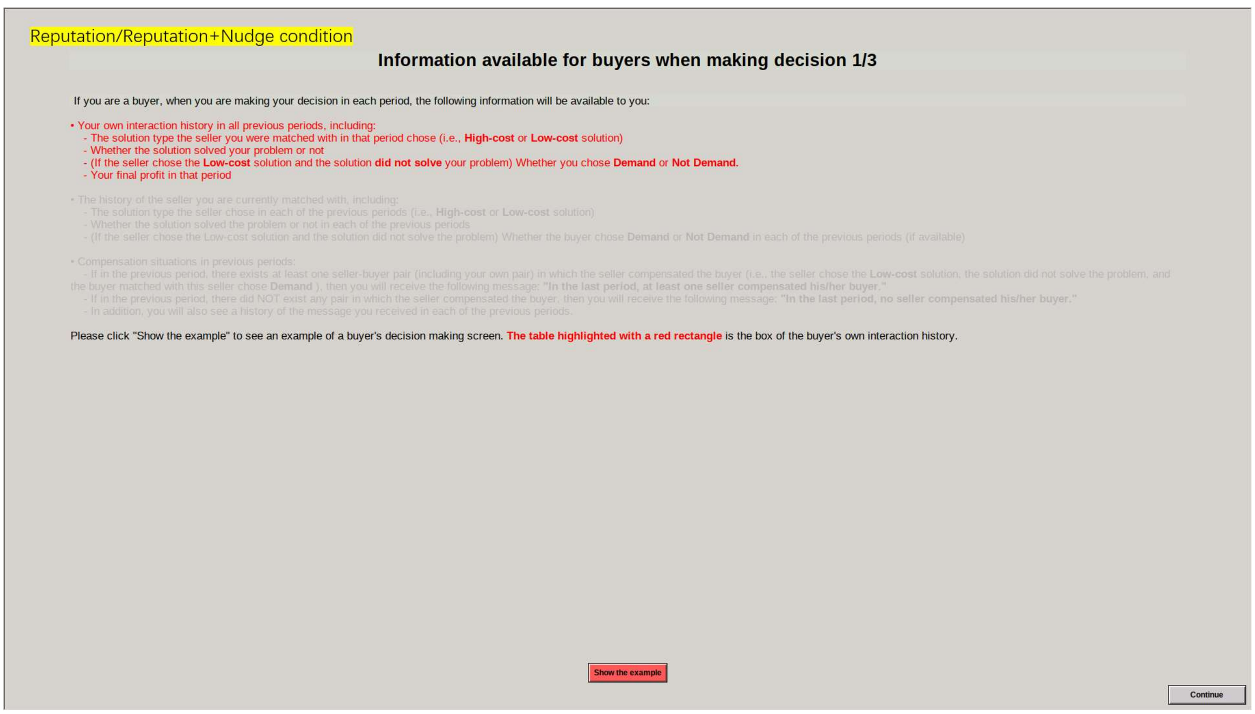
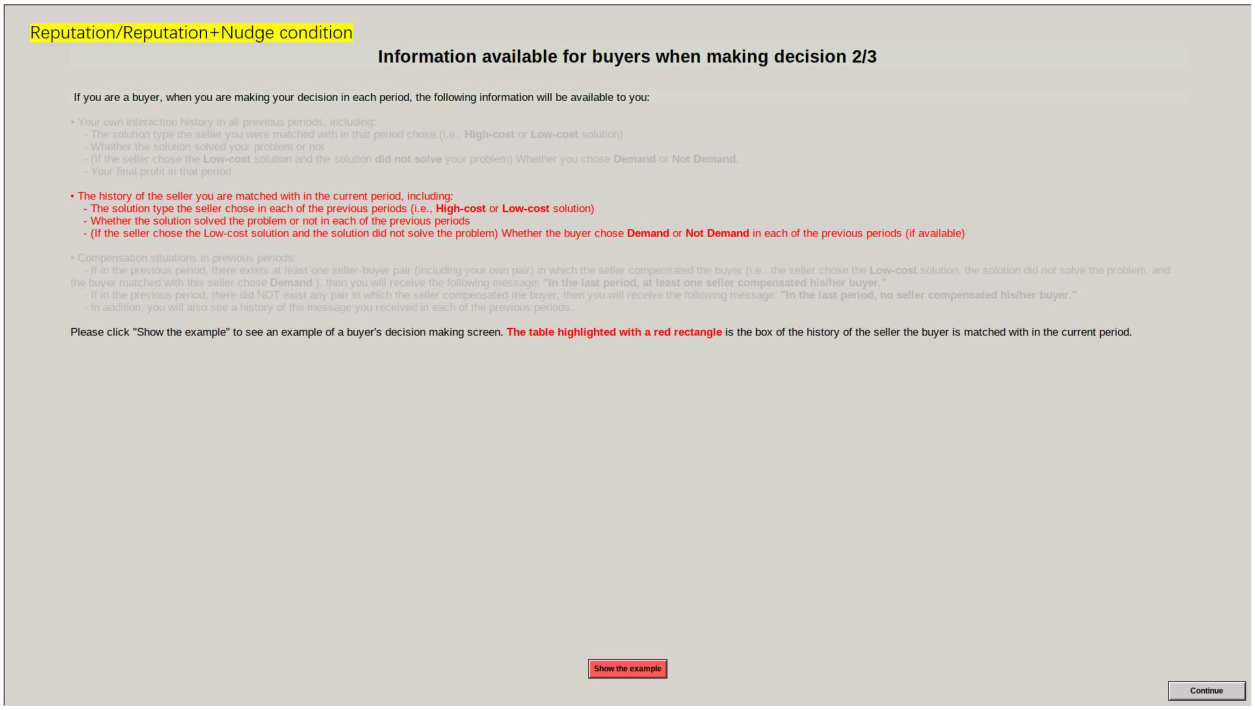


Figure 2.D.8. Experimental Instructions Screens 15-16



Reputation/Reputation+Nudge condition

Information available for buyers when making decision 2/3

If you are a buyer, when you are making your decision in each period, the following information will be available to you:

• Your own interaction history in all previous periods, including:
- The solution type the seller you were matched with in that period chose (i.e., **High-cost** or **Low-cost** solution)
- Whether the solution solved your problem or not
- (If the seller chose the **Low-cost** solution and the solution **did not solve** your problem) Whether you chose **Demand** or **Not Demand.**
- Your final profit in that period

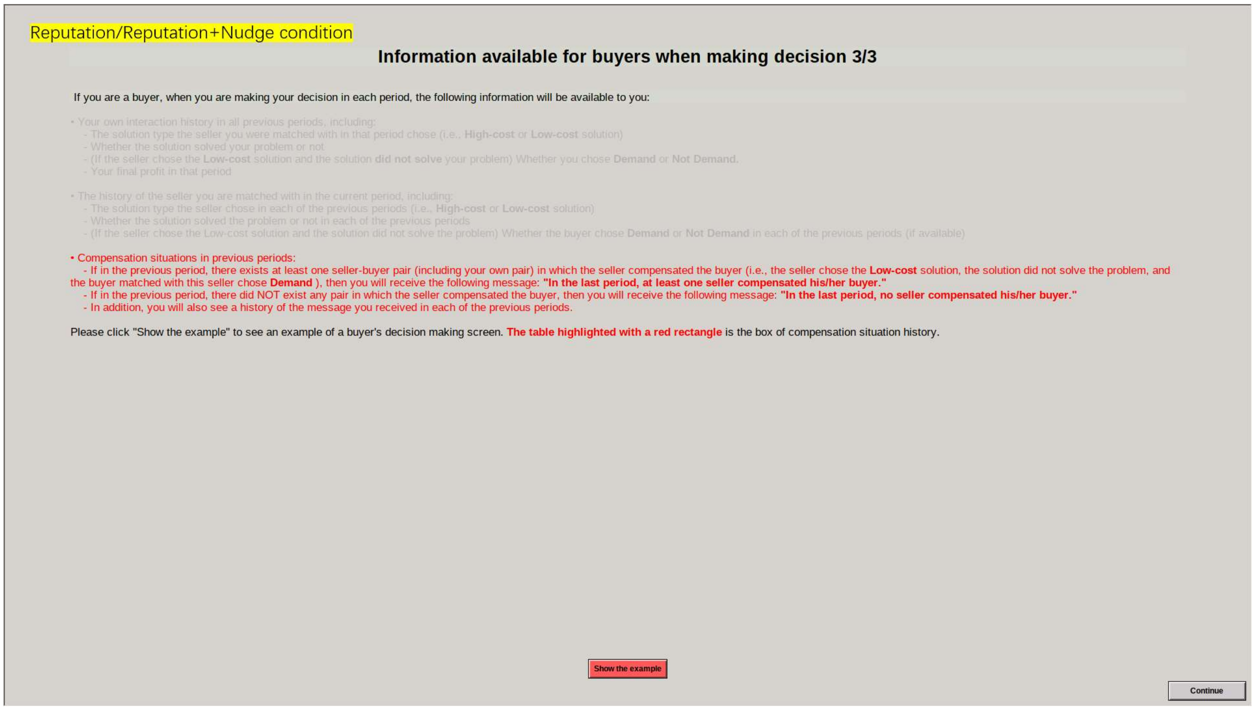
• The history of the seller you are matched with in the current period, including:
- The solution type the seller chose in each of the previous periods (i.e., **High-cost** or **Low-cost** solution)
- Whether the solution solved the problem or not in each of the previous periods
- (If the seller chose the Low-cost solution and the solution did not solve the problem) Whether the buyer chose **Demand** or **Not Demand** in each of the previous periods (if available)

• Compensation situations in previous periods:
- If in the previous period, there exists at least one seller-buyer pair (including your own pair) in which the seller compensated the buyer (i.e., the seller chose the **Low-cost** solution, the solution did not solve the problem, and the buyer matched with this seller chose **Demand**), then you will receive the following message: **"In the last period, at least one seller compensated his/her buyer."**
- If in the previous period, there did NOT exist any pair in which the seller compensated the buyer, then you will receive the following message: **"In the last period, no seller compensated his/her buyer."**
- In addition, you will also see a history of the message you received in each of the previous periods.

Please click "Show the example" to see an example of a buyer's decision making screen. **The table highlighted with a red rectangle** is the box of the history of the seller the buyer is matched with in the current period.

Show the example

Continue



Reputation/Reputation+Nudge condition

Information available for buyers when making decision 3/3

If you are a buyer, when you are making your decision in each period, the following information will be available to you:

• Your own interaction history in all previous periods, including:
- The solution type the seller you were matched with in that period chose (i.e., **High-cost** or **Low-cost** solution)
- Whether the solution solved your problem or not
- (If the seller chose the **Low-cost** solution and the solution **did not solve** your problem) Whether you chose **Demand** or **Not Demand.**
- Your final profit in that period

• The history of the seller you are matched with in the current period, including:
- The solution type the seller chose in each of the previous periods (i.e., **High-cost** or **Low-cost** solution)
- Whether the solution solved the problem or not in each of the previous periods
- (If the seller chose the Low-cost solution and the solution did not solve the problem) Whether the buyer chose **Demand** or **Not Demand** in each of the previous periods (if available)

• Compensation situations in previous periods:
- If in the previous period, there exists at least one seller-buyer pair (including your own pair) in which the seller compensated the buyer (i.e., the seller chose the **Low-cost** solution, the solution did not solve the problem, and the buyer matched with this seller chose **Demand**), then you will receive the following message: **"In the last period, at least one seller compensated his/her buyer."**
- If in the previous period, there did NOT exist any pair in which the seller compensated the buyer, then you will receive the following message: **"In the last period, no seller compensated his/her buyer."**
- In addition, you will also see a history of the message you received in each of the previous periods.

Please click "Show the example" to see an example of a buyer's decision making screen. **The table highlighted with a red rectangle** is the box of compensation situation history.

Show the example

Continue

Figure 2.D.9. Experimental Instructions Screens 17-18

Feedback at the end of each period

At the end of each period, sellers and buyers will receive the following feedback:

Each seller will receive the following feedback:

• The type of problem your buyer encountered (i.e., **Major** or **Minor** problem)

• The solution type you chose (i.e., **high-cost** solution or **low-cost** solution)

• Whether the solution solved the problem or not.

• (If you chose a **low-cost** solution and the solution did not solve the problem) Whether your buyer chose **Demand** or **Not Demand.**

• Your **final profit.**

Each buyer will receive the following feedback:

• The solution type your seller chose (i.e., **high-cost** solution or **low-cost** solution)

• Whether the solution solved your problem or not.

• (If your seller chose a **low-cost** solution and the solution did not solve your problem) Whether you chose **Demand** or **Not Demand.**

• Your **final profit.**

Continue

Sequence of steps in each period

Here is an overview of the sequence of steps each participant will go through in each period:

1. At the beginning of each period, the computer will randomly match one seller with one buyer (and the matching will be reshuffled in each period).

2. Each seller and buyer make his/her decision plan.

3. After all sellers and buyers submit their decision plans, the computer first rolls a virtual die to determine whether the buyer's problem is a major or minor one. The problem is a major one with a probability of 20% and a minor one with a probability of 80%.

4. Based on the seller's decision plan given the buyer's problem type, the computer implements a high-cost or low-cost solution.
• For example, if the buyer's problem is a major one, and the decision a seller submitted is *"if the buyer has a major problem then I choose a high-cost solution; if the buyer has a minor problem then I choose a low-cost solution"*, then the computer will implement a high-cost solution.

5. The computer determines whether the seller's solution solves the buyer's problem or not based on the probability distribution described below:

	Major problem (20% occurrence)	**Minor** problem (80% occurrence)
High-cost solution	87.5% Solved 12.5% Not Solved	100% Solved 0% Not Solved
Low-cost solution	12.5% Solved 87.5% Not Solved	87.5% Solved 12.5% Solved

6. If and only if the seller's solution is a **low-cost** solution and it **does NOT solve** the buyer's problem, then the computer implements the buyer's decision of whether to ask the seller to compensate or not.

7. Each seller's and buyer's final profit in the current period are determined, which can be described by the graph below.

Show the graph

Continue

Figure 2.D.10. Experimental Instructions Screens 19-20

Expected final profits of each seller and buyer

As we can see from previous pages, the seller has 4 options while the buyer has 2 options. This makes 4*2=8 possible combinations of options in total, as demonstrated below:

	If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Demand				
Not Demand				

In order to help you have a general impression of how much **final profit** you can earn **on average** for each of the 8 option combinations, we help you calculate the **expected final profit** of each of these 8 option combinations.

In mathematics, the **expected final profit** equals a weighted sum of your payoff in all possible cases, and the weight is the probability of the occurrence of that case.

The table below summarizes the expected final profits of all 8 option combinations.

For example, the first cell tells us that if the seller's decision plan is *"If it is a major problem, then I choose a high-cost solution; if it is a minor problem, then I choose a high-cost solution"* and the buyer's decision plan is *"Demand"* , then the seller's **expected final profit** is 40 and the buyer's **expected final profit** is 37.

			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

Please note that this table of expected final profits is only a calculation of how much you can earn **on average** (across all possible situations) in each of the 8 option combinations, but NOT how much you can *actually* earn.

Continue

Comprehension Questions 1/6

To ensure that you have fully understood the instructions of this experiment, you will be asked to answer several comprehension questions. You have unlimited number of attempts to correctly answer each question, but you have to correctly answer all of them in order to proceed to the experiment. In addition, you will receive 80 ECUs for correctly answering them.

Question 1:

Suppose in a certain period, a seller makes the following choices:

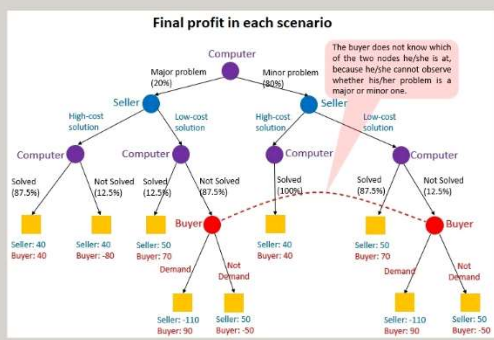
Please choose which solution type you will use, if the buyer has a **major** problem:
- ○ High-cost solution
- ● Low-cost solution

Please choose which solution type you will use, if the buyer has a **minor** problem:
- ● High-cost solution
- ○ Low-cost solution

Also suppose that in the same period, the buyer matched with this seller makes the following choice:

Please choose from the following two options, if the seller chooses the **low-cost** solution and your problem is NOT solved:

- ● Demand: "The seller should compensate me!"
- ○ Not Demand: "I do not ask the seller to compensate me."



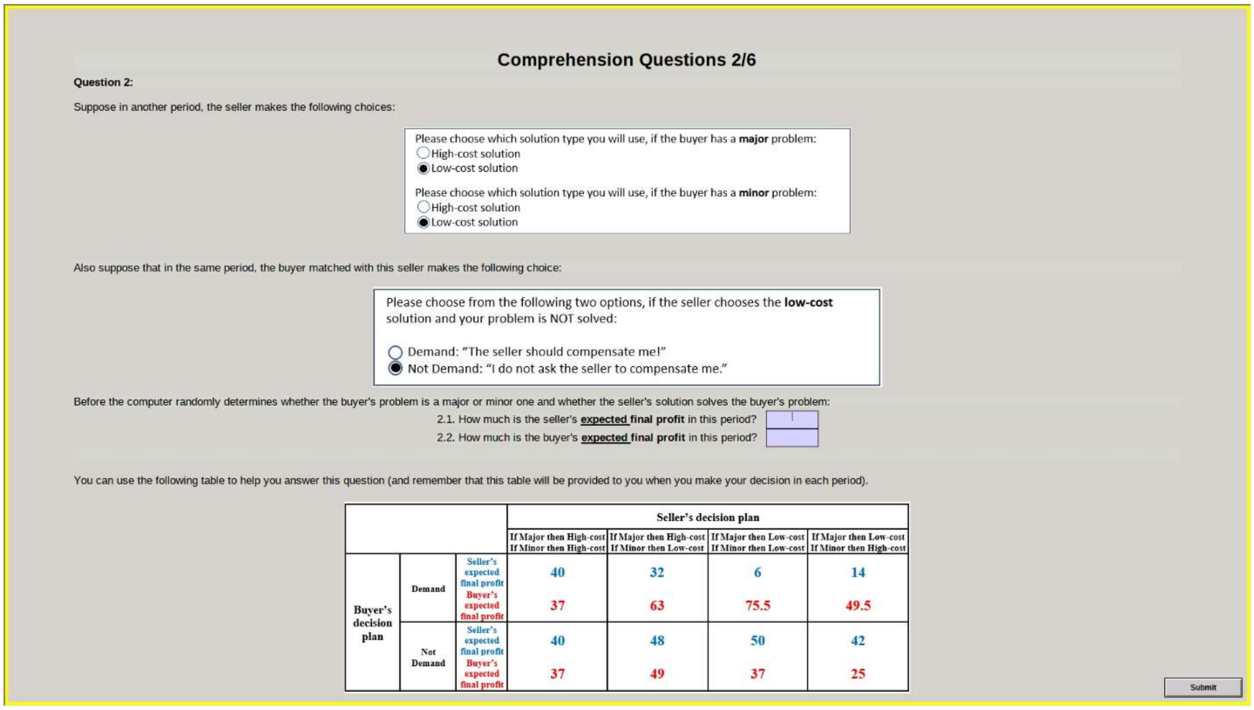
Suppose that the computer randomly determines that the buyer's problem is a **major** one, and the seller's solution **does NOT** solve the problem.

1.1. How much is the seller's final profit in this period (ECUs)?

1.2. How much is the buyer's final profit in this period (ECUs)?

Submit

Figure 2.D.11. Experimental Instructions Screens 21-22



Comprehension Questions 2/6

Question 2:

Suppose in another period, the seller makes the following choices:

Please choose which solution type you will use, if the buyer has a **major** problem:
○ High-cost solution
● Low-cost solution

Please choose which solution type you will use, if the buyer has a **minor** problem:
○ High-cost solution
● Low-cost solution

Also suppose that in the same period, the buyer matched with this seller makes the following choice:

Please choose from the following two options, if the seller chooses the **low-cost** solution and your problem is NOT solved:

○ Demand: "The seller should compensate me!"
● Not Demand: "I do not ask the seller to compensate me."

Before the computer randomly determines whether the buyer's problem is a major or minor one and whether the seller's solution solves the buyer's problem:

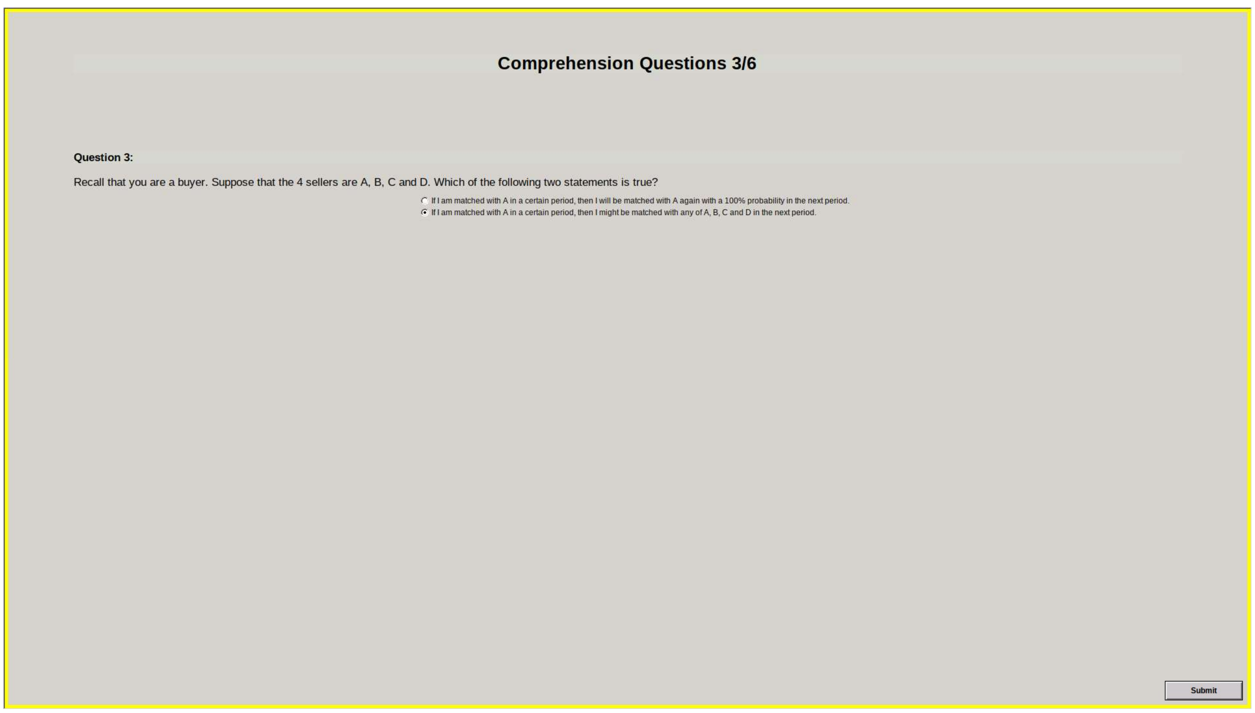
2.1. How much is the seller's **expected final profit** in this period?

2.2. How much is the buyer's **expected final profit** in this period?

You can use the following table to help you answer this question (and remember that this table will be provided to you when you make your decision in each period).

			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

Submit



Comprehension Questions 3/6

Question 3:

Recall that you are a buyer. Suppose that the 4 sellers are A, B, C and D. Which of the following two statements is true?

○ If I am matched with A in a certain period, then I will be matched with A again with a 100% probability in the next period.
● If I am matched with A in a certain period, then I might be matched with any of A, B, C and D in the next period.

Submit

Figure 2.D.12. Experimental Instructions Screens 23-24

Comprehension Questions 4/6

Question 4:

How many periods will this game be repeated for?

A. This game will be repeated for 60 periods.

B. This game will be repeated for 60 periods for sure, and then starting from Period 61, a virtual die will be rolled at the end of each period. With a probability of 90%, the game will continue to the next period. With a probability of 10%, the game will end.

- A
- B

Submit

Reputation/Reputation+Nudge condition

Comprehension Questions 5/6

Question 5:

When a **seller** is making his decision in each period, he/she is able to observe whether any seller on the market compensated his/her buyer in each of the previous periods. Is this true or false?

- True
- False

Submit

Figure 2.D.13. Experimental Instructions Screens 25-26

Reputation/Reputation+Nudge condition

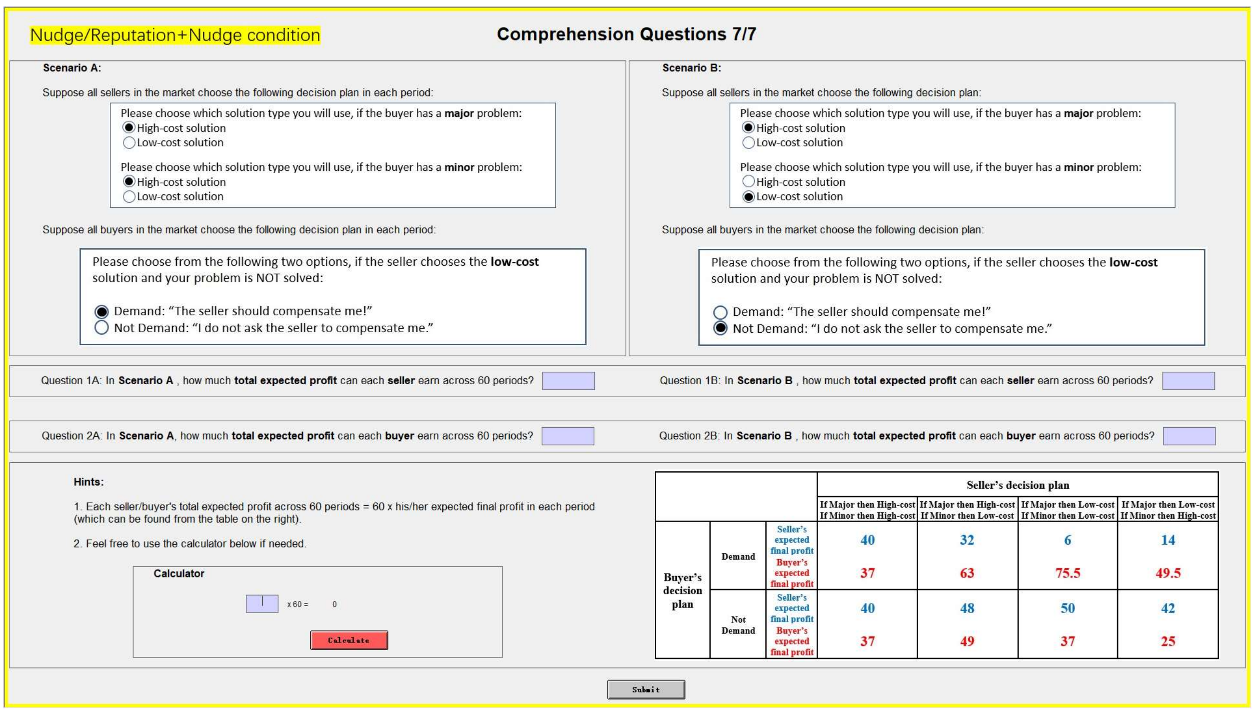
Comprehension Questions 6/6

Question 6:

Suppose that a certain seller is randomly matched with a certain buyer in a period. When the buyer is making his/her decision, he/she is able to observe the seller's history in each of the previous periods (i.e., the solution type this seller chose, whether the seller solved the problem or not, and the reaction of the buyer matched with this seller in that period, if available) and whether any seller on the market compensated his/her buyer in each of the previous periods. Is this true or false?

- True
- False

Submit



Nudge/Reputation+Nudge condition

Comprehension Questions 7/7

Scenario A:

Suppose all sellers in the market choose the following decision plan in each period:

Please choose which solution type you will use, if the buyer has a **major** problem:
- (•) High-cost solution
- ( ) Low-cost solution

Please choose which solution type you will use, if the buyer has a **minor** problem:
- (•) High-cost solution
- ( ) Low-cost solution

Suppose all buyers in the market choose the following decision plan in each period:

Please choose from the following two options, if the seller chooses the **low-cost** solution and your problem is NOT solved:

- (•) Demand: "The seller should compensate me!"
- ( ) Not Demand: "I do not ask the seller to compensate me."

Scenario B:

Suppose all sellers in the market choose the following decision plan:

Please choose which solution type you will use, if the buyer has a **major** problem:
- (•) High-cost solution
- ( ) Low-cost solution

Please choose which solution type you will use, if the buyer has a **minor** problem:
- ( ) High-cost solution
- (•) Low-cost solution

Suppose all buyers in the market choose the following decision plan:

Please choose from the following two options, if the seller chooses the **low-cost** solution and your problem is NOT solved:

- ( ) Demand: "The seller should compensate me!"
- (•) Not Demand: "I do not ask the seller to compensate me."

Question 1A: In **Scenario A** , how much **total expected profit** can each **seller** earn across 60 periods?

Question 1B: In **Scenario B** , how much **total expected profit** can each **seller** earn across 60 periods?

Question 2A: In **Scenario A**, how much **total expected profit** can each **buyer** earn across 60 periods?

Question 2B: In **Scenario B** , how much **total expected profit** can each **buyer** earn across 60 periods?

Hints:

1. Each seller/buyer's total expected profit across 60 periods = 60 x his/her expected final profit in each period (which can be found from the table on the right).

2. Feel free to use the calculator below if needed.

Calculator

x 60 = 0

Calculate

			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

Submit

Figure 2.D.14. Experimental Instructions Screens 27-28

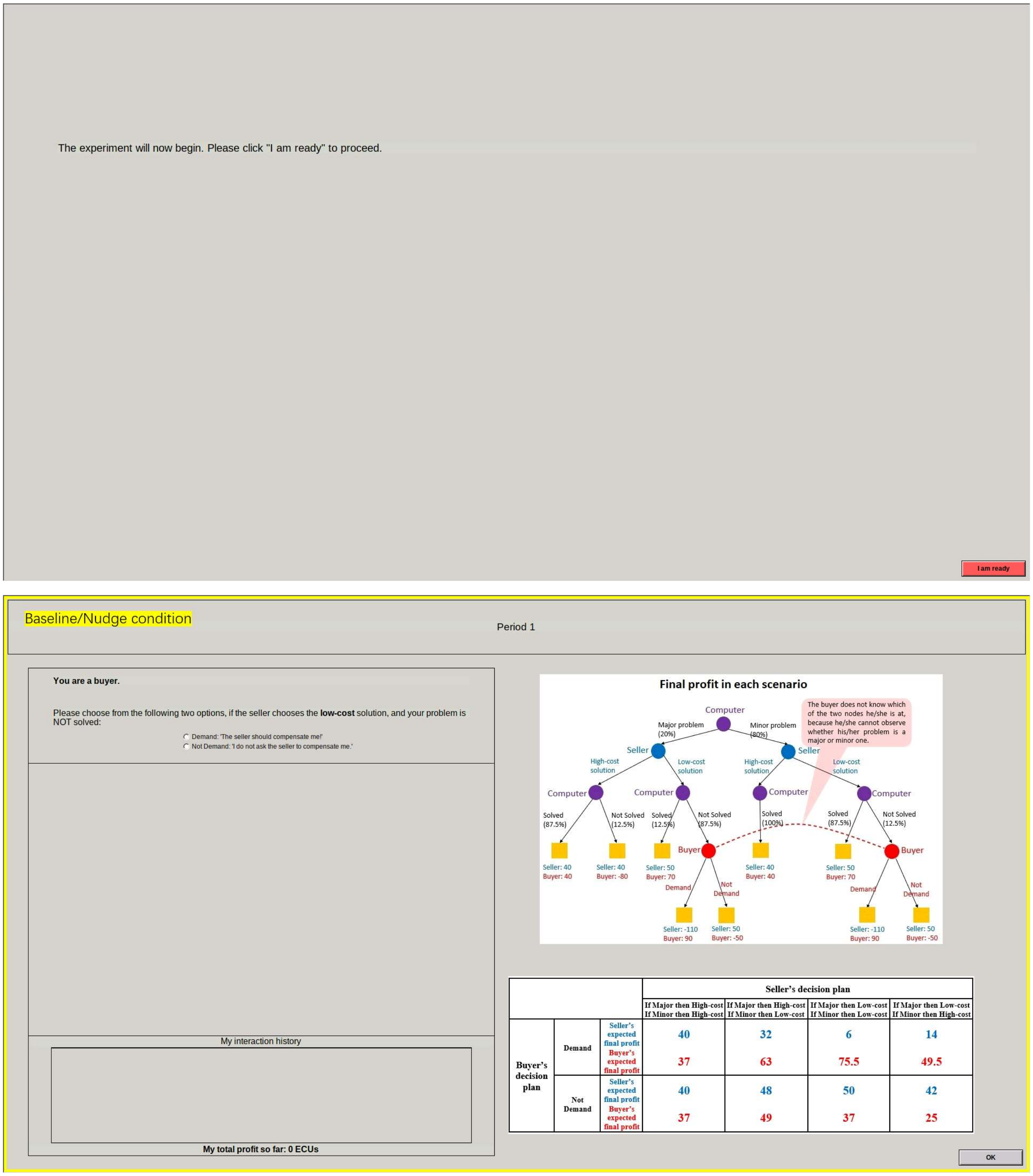


Figure 2.D.15. Experimental Instructions Screens 29-30

Baseline/Nudge condition

Period 1

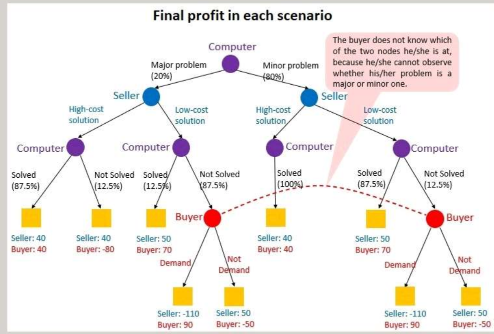
You are a seller.

Please choose which solution type you will use, if the buyer has a **major** problem:

- High-cost solution
- Low-cost solution

Please choose which solution type you will use, if the buyer has a **minor** problem:

- High-cost solution
- Low-cost solution



			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

My interaction history

My total profit so far: 0 ECUs

OK

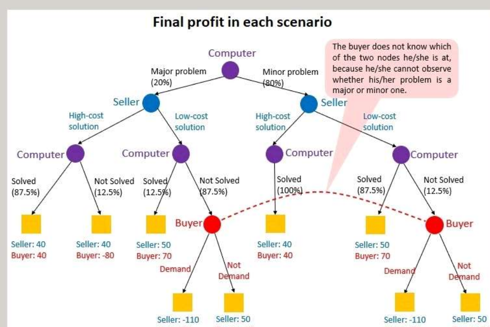
Reputation/Reputation+Nudge condition

Period 1

You are a buyer.

Please choose from the following two options, if the seller chooses the **low-cost** solution, and your problem is NOT solved:

- Demand: 'The seller should compensate me!'
- Not Demand: 'I do not ask the seller to compensate me.'



			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

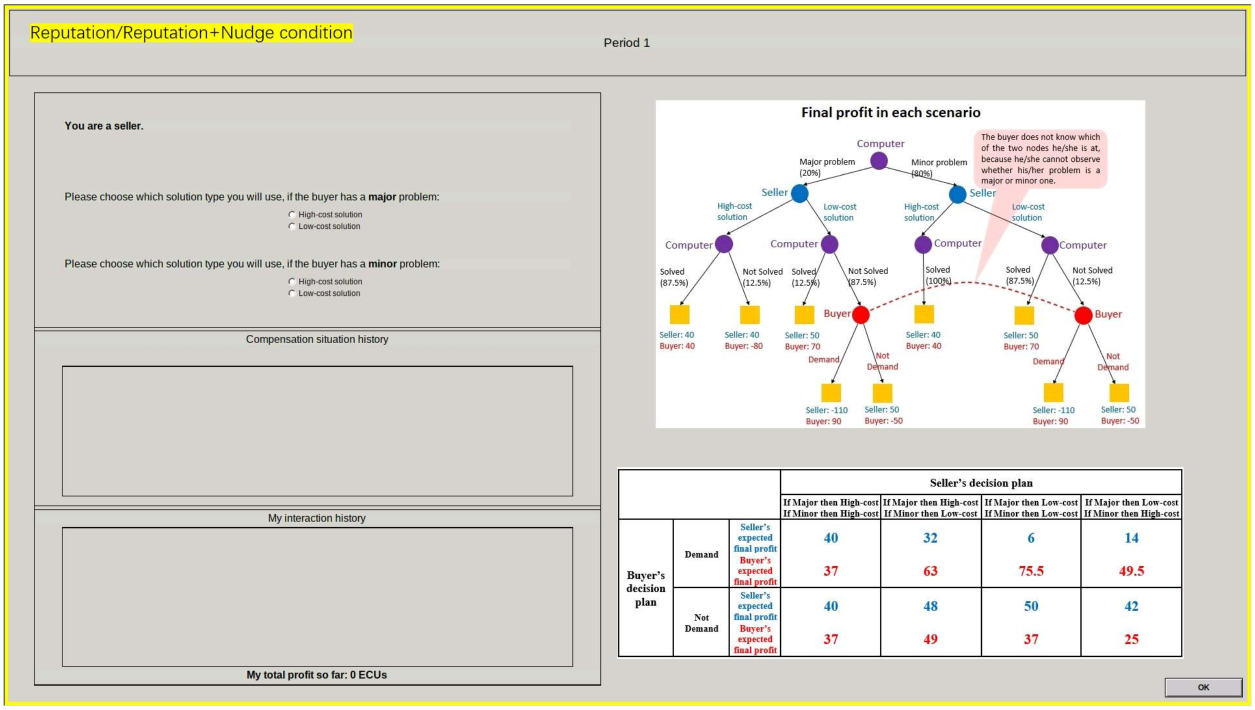
Compensation situation history

My interaction history

My total profit so far: 0 ECUs

OK

Figure 2.D.16. Experimental Instructions Screens 31-32



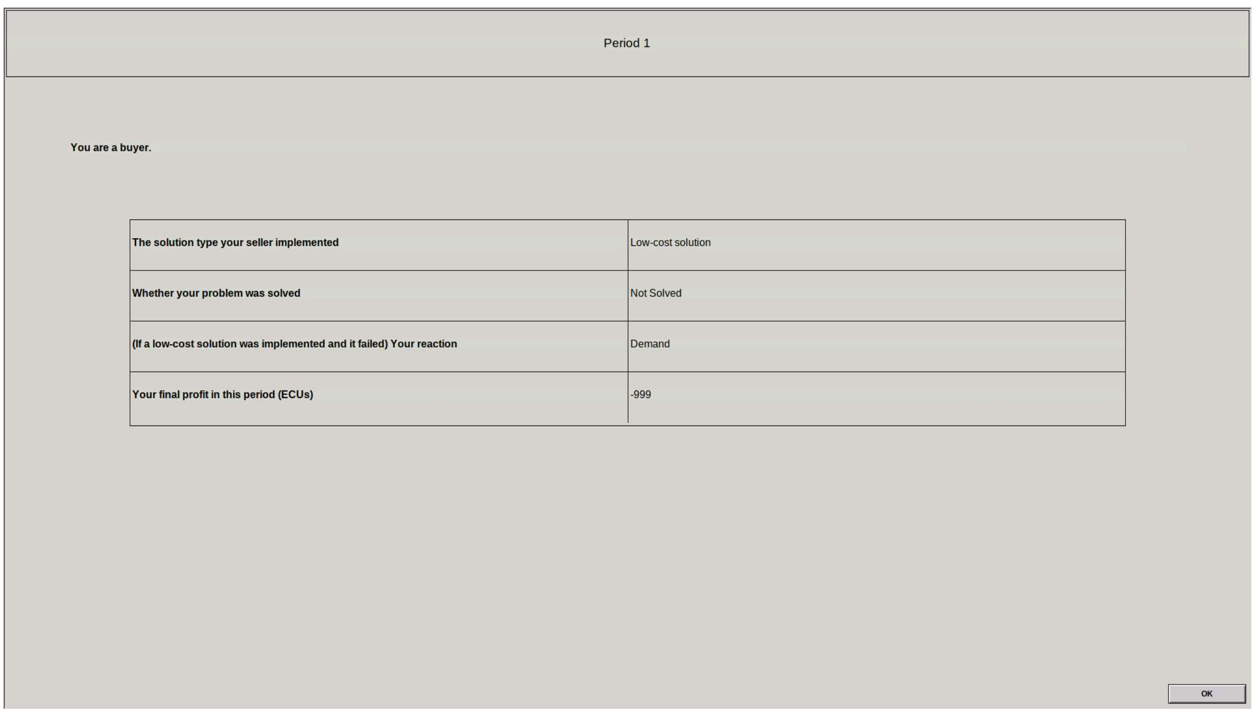


Figure 2.D.17. Experimental Instructions Screens 33-34

Period 1

You are a seller.

The buyer's problem type	Minor
The solution type implemented based on your decision	Low-cost solution
Whether the buyer's problem was solved	Not Solved
(If a low-cost solution was implemented and it failed) The buyer's reaction	N/A
Your final profit in this period (ECUs)	-999

OK

Post-experiment Survey 1/3

Please answer the following questions:

If your seller identifies that your problem is a **major** one, what do you think is the most socially appropriate solution type your seller should choose?

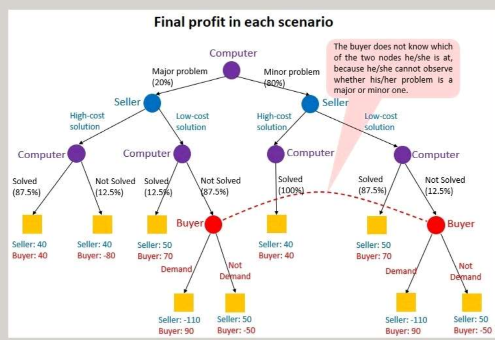
- High-cost solution
- Low-cost solution

If your seller identifies that your problem is a **minor** one, what do you think is the most socially appropriate solution type your seller should choose?

- High-cost solution
- Low-cost solution

If your seller chooses a low-cost solution and it fails, what do you think your seller thinks is the most socially appropriate action you should take?

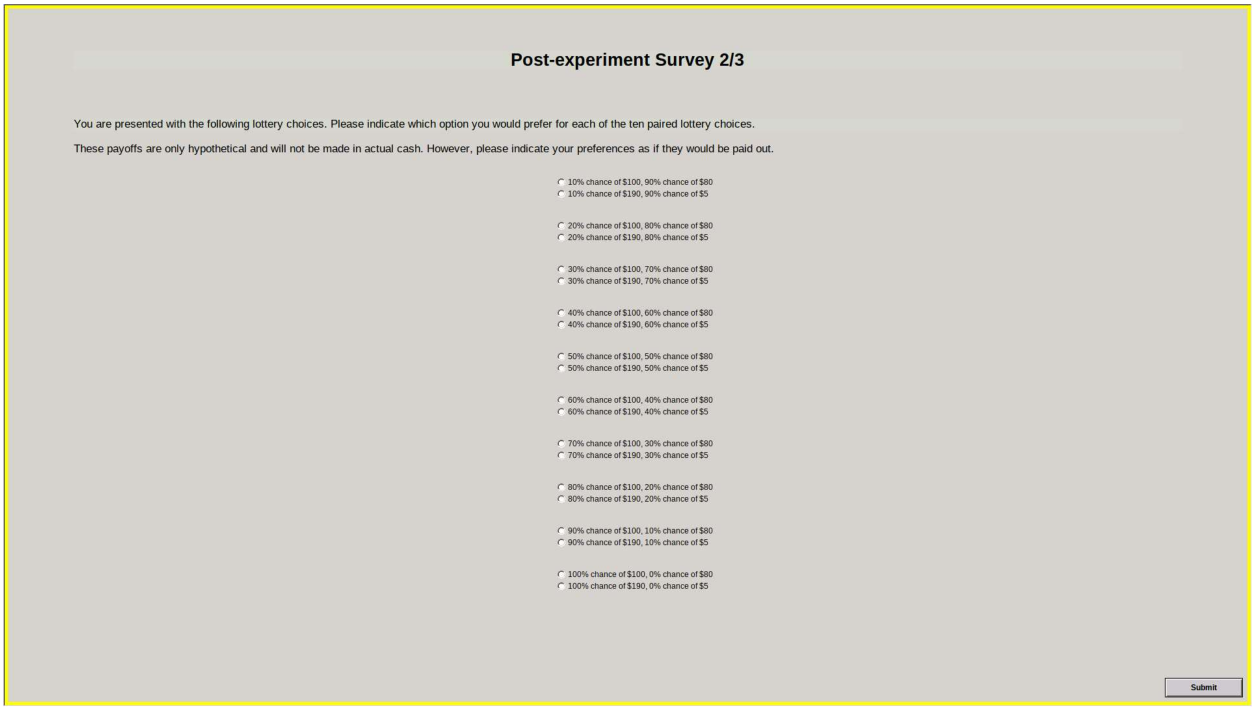
- Demand: 'The seller should compensate me!'
- Not Demand: 'I do not ask the seller to compensate me!'



			Seller's decision plan			
			If Major then High-cost If Minor then High-cost	If Major then High-cost If Minor then Low-cost	If Major then Low-cost If Minor then Low-cost	If Major then Low-cost If Minor then High-cost
Buyer's decision plan	Demand	Seller's expected final profit	40	32	6	14
		Buyer's expected final profit	37	63	75.5	49.5
	Not Demand	Seller's expected final profit	40	48	50	42
		Buyer's expected final profit	37	49	37	25

Submit

Figure 2.D.18. Experimental Instructions Screens 35-36



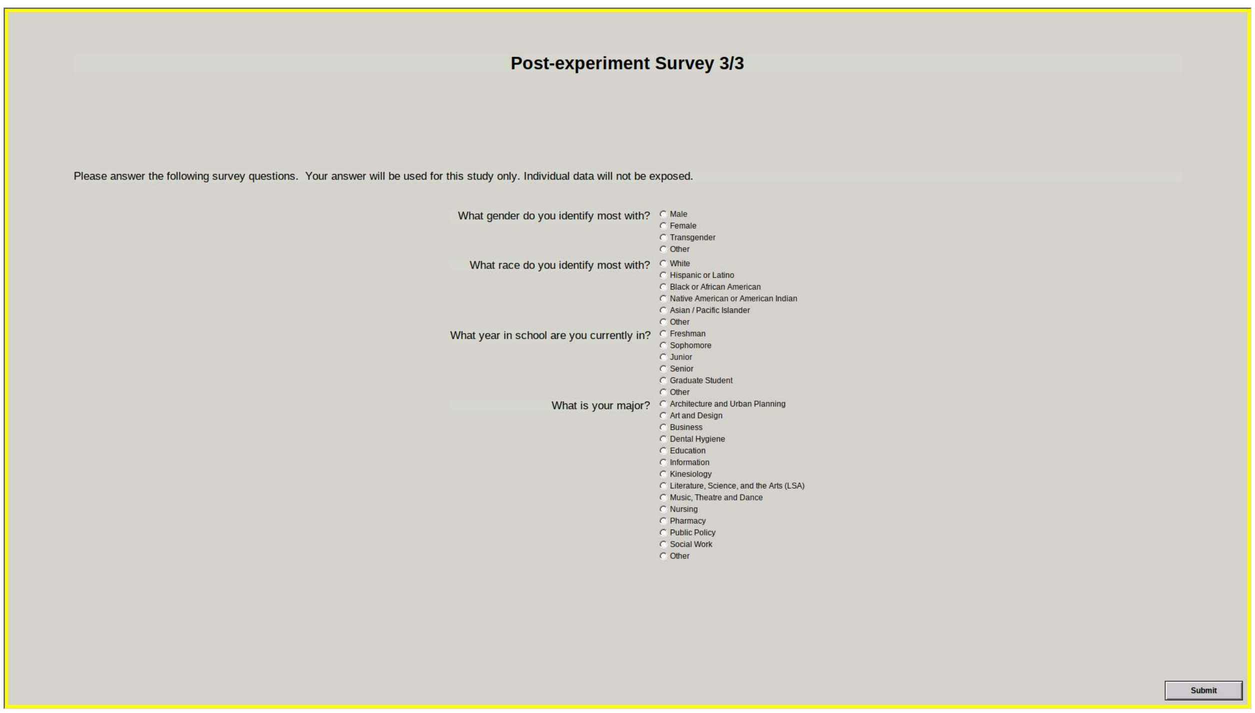


Figure 2.D.19. Experimental Instructions Screens 37-38

Chapter 3: How to Make Better and/or Cheaper Products Accessible to Buyers through an Optimal Product Testing Mechanism

3.1. Introduction

In many markets, buyers are less informed about the quality of a product than sellers are. As Akerlof (1970) indicates, this asymmetric information about vertical product quality[42] may decrease consumer surplus.[43] Independent product quality testing organizations[44] such as Consumer Reports (US), Stiftung Warentest (Germany), and Which? (UK) are third-party certifiers who mitigate buyers' informational disadvantage by providing credible information about product quality. They are usually not-for-profit organizations who neither require sellers to pay a fee for the rating service, nor accept advertisements in order to avoid conflicts of interest (see Consumer Reports,

[42] As Vollstaedt et al. (2020) note, product quality is a multidimensional construct that measures the extent to which the product satisfies a consumer's needs. It consists of both horizontal and vertical dimensions. Consumers differ in their preferences with respect to horizontal quality dimensions (Hotelling, 1929). For example, one horizontal dimension of a stroller's quality is its color. Consumers could have different preferences over colors. In contrast, consumers' preferences with respect to vertical quality dimensions are universally aligned, and these dimensions are objectively measurable. For instance, as for a stroller, its weight, waterproofness and the level of toxic materials are vertical dimensions. Consumers will universally prefer a stroller with less toxic substance to another one with more toxic substance. It should also be noted that these vertical dimensions often include search, experience, and credence features (Nelson, 1970; Darby & Karni, 1973). In the example of a stroller, its weight, waterproofness and the level of toxic materials are search, experience and credence features respectively.

[43] We follow Vollstaedt et al. (2020) in noting that, while most products contain some amount of horizontal and some amount of vertical quality dimensions, the relevance of each one may differ. This paper focuses on products whose vertical quality dimensions are at least as relevant for buyers as its horizontal ones, e.g., toothpaste, strollers, or grills. We do not analyze markets for products whose horizontal quality dimensions are more relevant for buyers than its vertical ones, e.g., fiction movies or books. Note that, while online consumer ratings for such products can be found on websites like amazon.com or imdb.com, independent product quality testing organizations usually do not test fiction movies or books.

[44] Hereafter, testing organization.

Stiftung Warentest (2019), and Which?). Instead, they finance themselves mainly through selling their own publications (International Consumer Research & Testing).[45] As Vollstaedt et al. (2020) note, testing organizations usually aim to offer an overall rating of *vertical* product quality, [46] and they are usually widely known and have a good reputation. [47] Consequently, information provided by testing organizations is very close to what Viscusi (1978) proposed in a reply to Akerlof (1970), namely to provide *credible* information to buyers.[48] [49]

Despite their ability to provide credible information about vertical product quality, testing organizations often have limited testing capacities. Specifically, for a certain product, testing organizations are only capable of selecting and testing a fraction of product models that are available on the market.[50] [51] They often use their limited capacity to test products that appear to be preferred by consumers. For example, Stiftung Warentest chooses bestsellers, based on current sales numbers, for testing. They usually select 2 % to 33 % of all available products for testing (as in the 09/2016 magazine, see GfK SE). Consumer Reports and Which? consider a series of factors including sales numbers and price.

A recent paper investigates how different product selection mechanisms influence consumer surplus in the short term, i.e., when quality and price are exogenous (Vollstaedt et al., 2020). They show that, when quality and price have already been set, any current selection mechanism

[45] Refer to http://www.international-testing.org/members.html for a list of international testing organizations.

[46] Often, testing organizations employ their own test buyers to be able to buy products anonymously. To obtain an overall rating, testing organizations assign a weight on each quality dimension, test and rate each dimension, and then calculate a weighted sum of all dimensions. Test results are accessible online or in print magazines.

[47] For example, 96 % (77 %) of German consumers know of (strongly trust) Stiftung Warentest (KantarEmnid and Verbraucherzentrale Bundesverband, p. 9). There are more than 6 million paying members of Consumer Reports in the US, and on average there are 14 million unique visits to their website every month (Consumer Reports).

[48] As Vollstaedt et al. (2020) note, buyers also use other proxies for quality, e.g., online consumer ratings (Rao & Monroe, 1989; De Langhe et al., 2016). Online consumer ratings are often readily available. However, they are problematic since, first, they usually do not include credence characteristics, e.g., toxic substances in food, cosmetics, or clothing, or under which working conditions a product was manufactured. Second, online consumer ratings often include both vertical and horizontal quality dimensions although the latter are, by definition, not objectively rateable. Third, a considerable number of fake ratings exist, even among verified purchases (Mayzlin et al., 2014; Which?, 2018). Interestingly, online consumer ratings correlate poorly with ratings provided by testing organizations (De Langhe et al., 2016; Köcher & Köcher, 2018).

[49] Price is a commonly used proxy for product quality. However, previous literature shows that it seems to be a weak proxy (see Ratchford et al., 1996; Oxenfeldt, 1950; De Langhe et al., 2016; Diller, 1977, 1988; Yamada & Ackerman, 1984; Bodell et al., 1986; Steenkamp, 1988; Kirchler et al., 2010, and Olbrich & Jansen, 2014 for overviews).

[50] Note that a certain type of product may have different product models. For example, a smartphone can have several smartphone models. However, to improve readibility, we use "product" instead of "product model" hereafter.

[51] Testing organizations do not only face capacity constraints as to which *product models*, but also as to which *products* to select for testing. This study focuses on the problem of which *product models* to select.

almost always provides suboptimal information for consumers. Instead, they propose a new mechanism which (weakly) dominates any current mechanism. More precisely, under this new mechanism, all products that buyers would have selected under complete information are selected for testing, yielding optimal consumer surplus.

In this paper, we investigate whether our proposed product testing mechanism SELLERS-MAYAPPLY can maximize consumer surplus when sellers endogenously determine the price and quality of their products. We build a theoretical model for a product testing game. In this game, sellers make production, pricing and quality testing application decisions, and then a testing organization uses our proposed product testing mechanism to determine which seller(s)' products to test and reveal their qualities to buyers. Finally, buyers make purchasing decisions based on the qualities revealed by the testing organization and all sellers' prices. We prove that in all pure-strategy weak Perfect Bayesian Equilibria, all buyers purchase products that maximize their surplus. Therefore, our proposed product testing mechanism (weakly) dominates any other alternative product testing mechanism.

In addition to the SELLERSMAYAPPLY condition in which our proposed mechanism is applied, we also consider a RANDOMTESTING condition in which the testing organization randomly tests the same number of products and reveals their qualities to buyers. The RANDOMTESTING mechanism is a generic testing mechanism in which sellers cannot affect whether their products will be tested.

We conduct a laboratory experiment to test the effectiveness of our proposed SELLERS-MAYAPPLY mechanism. We find that consumer surplus is significantly higher when we use our SELLERSMAYAPPLY mechanism than when we use the RANDOMTESTING mechanism.

This study contributes to the theoretical literature in industrial organization in two important aspects. First, we show that we can incentivize sellers to offer products that maximize consumer surplus through a product testing mechanism in which sellers can influence whether and with what probability their products will be tested. Second, we include a testing organization as a means to provide credible information for buyers and, most fundamentally, allow for prices which may *not* be positively correlated with quality.

There have been theoretical, empirical and experimental studies that investigate the effectiveness of unraveling and information diclosure (see Dranove & Jin, 2010, and Brendel, 2021 for overviews). Some theoretical studies indicate that full unraveling is usually difficult to achieve due to its requirement for some strong assumptions (e.g., Grossman, 1981; Milgrom, 1981). However, there have been some empirical studies that find unraveling to an incomplete degree (e.g., Mathios, 2000; Jin & Leslie, 2003), and there is also experimental evidence showing both unraveling to an incompleted degree (e.g., Benndorf et al., 2015; Benndorf, 2018) and unraveling to a complete degree when feedback and learning are allowed (e.g., Forsythe et al., 1989; Jin et al., 2021). To the best of our knowledge, our study is the first one that investigates whether unraveling increases market efficiency in the long term (i.e., prices and qualities are endogenous) when there are limited information disclosure capacities.

We also contribute to the literature on third-party certifiers by considering testing organizations that are different from other third-party certifiers in several aspects. First, we consider not-for-profit testing organzations which do not charge fees for the purpose of increasing their own profits. These organizations are different from private third-party certifiers such as Moody's and PSA[52], which charge sellers a fee for the rating service (Dranove & Jin, 2010; List, 2006; Jin et al., 2010). Because of the not-for-profit feature, testing organizations do not have the incentive to give overgenerous ratings in exchange for future business. Second, due to the not-for-profit property, independent product testing organzations often have limited testing capacities, which are different from private third-party certifiers such as Moody's and PSA and other non-profit third-party certifiers such as USDA organic or Blauer Engel.

The rest of our paper proceeds as follows. Section 3.2 introduces our theoretical framework and derives our theoretical predictions. Section 3.3 presents our experimental design and hypotheses. Section 3.4 reports our experimental results. Section 3.5 discusses our findings and concludes.

3.2. Theory

In this section, we first establish settings for the market (Section 3.2.1) and then make predictions (Section 3.2.2).

[52] Professional Sports Authenticator (PSA) is one of the largest card grading services world-wide (for more information, see https://www.psacard.com/services/tradingcardgrading).

3.2.1. Market Settings

We consider a market with a non-empty set of rational sellers F, with $\emptyset \neq F = \{f_1, \ldots, f_n\}$ and $n \geqslant 6$, and a non-empty set of rational buyers B, with $\emptyset \neq B = \{b_1, \ldots, b_s\}$ and $s \geqslant 2$.

3.2.1.1. Sellers

Each seller f_i offers products with a certain quality level $q_i \in \{1, 2, 3\}$ and a price $p_i \in \mathbb{R}^+$. We assume each seller can sell as many units of that product as demanded, but all the products she sells must be identical in quality and price. The marginal cost c_i is a function of quality q_i, i.e., $c_i = c(q_i)$. The marginal cost function is assumed to be continuously differentiable, strictly increasing and strictly convex in quality, i.e., $c'\big(q_i\big) > 0$ and $c''\big(q_i\big) > 0$. Since we are not interested in analyzing market entry or exit decisions and since positive fixed costs would thus not influence equilibrium predictions, we assume all sellers' fixed costs equal zero. Each seller f_i's payoff function is

$$\pi_i\big(p_i, q_i\big) = \Big(p_i - c\big(q_i\big)\Big)d_i \tag{82}$$

where d_i represents the demand for f_i's product, i.e., the number of buyers buying seller f_i's product.

3.2.1.2. Buyers

Each buyer decides whether, and if so from which seller, to buy at most one product. They are not able to resell. Different buyers may have different valuations for the quality of a product. For buyer b_j, with $j \in \{1, \ldots, s\}$, we call θ_j her valuation of quality, with $0 < \theta_j \in \mathbb{R}^+$. Among all buyers, there are two types of buyers with two different θ values: θ_L or θ_H. The numbers of buyers with $\theta_j = \theta_L$ and $\theta_j = \theta_H$ are the same. If a buyer decides to buy a product from seller f_i, then her payoff function is

$$\pi_j\big(p_i, q_i, \theta_j\big) = \theta_j q_i - p_i \tag{83}$$

$\theta_j q_i$ is a buyer's willingness to pay for q_i. Finally, if a buyer chooses not to purchase a product model, her payoff is zero. Buyers with different valuation of quality θ have different preferred product qualities when all products with different qualities have a markup of 0 (in other words, when the prices of all products are equal to their corresponding marginal cost). Specifically, buyers with $\theta = \theta_L$ strictly prefer a quality 2 product, while buyers with $\theta = \theta_H$ strictly prefer a quality 3 product, if all products with different qualities have a markup of zero.[53] Formally, we have

$$\arg\max_{q \in \{1,2,3\}} \theta_L q - c(q) = 2 \tag{84}$$

$$\arg\max_{q \in \{1,2,3\}} \theta_H q - c(q) = 3 \tag{85}$$

The two equations (84) and (85) have the following implications:

$$2\theta_L - c(2) > \theta_L - c(1) \Leftrightarrow c(2) - c(1) < \theta_L \tag{86}$$

$$2\theta_L - c(2) > 3\theta_L - c(3) \Leftrightarrow c(3) - c(2) > \theta_L \tag{87}$$

$$3\theta_H - c(3) > \theta_L - c(1) \Leftrightarrow c(3) - c(1) < 2\theta_H \tag{88}$$

$$3\theta_H - c(3) > \theta_H - c(2) \Leftrightarrow c(3) - c(2) < \theta_H \tag{89}$$

3.2.1.3. Testing Organization

After all sellers determine the qualities and prices of their products, the prices of all sellers are visible to each buyer (and each seller and the testing organization). However, the quality of a seller's product is visible to each buyer if and only if the product has been tested by the testing organization and the organization reveals the quality of the product. The testing organization can accurately find out the true quality of a product after the test, but the organization has a limited maximum testing capacity $k \in \mathbb{N}$. It selects at most k sellers' products according to a certain product selection mechanism. In this study, we consider a case in which the maximum testing capacity is 2, which is equal to the number of quality levels preferred by the two types of buyers when all products have a markup of 0. Denote the set of products that are selected by the organization to be tested as K, and denote the set of products whose qualities are revealed to buyers by the organization as K'. There is $K' \subseteq K \subseteq F$. In this study, we consider two product selection

[53] Note that, if offered at marginal costs, no buyer would select quality level 1 which corresponds to a "poor" rating. This rating is given when a product is considered unacceptable for all, as when it does not suit its claimed purpose and/or entails unacceptable risks such as high toxic material levels.

mechanisms: our proposed mechanism SELLERSMAYAPPLY and a random selection mechanism RANDOMTESTING. The latter mechanism represents a stylized version of mechanisms in which sellers cannot directly influence whether their products will be tested. We assume both mechanisms are testing capacity-neutral, i.e., they provide the same number of testing slots. We refrain from modeling the testing organization's payoff function since, as mentioned above (Section 3.1), it is a non-profit organization which does not rely on fees for the rating service. Since we model the testing organization as an algorithm without its own surplus function, we do not call it a player.

3.2.1.4. The Two Product Testing Mechanisms

This subsection introduces how the testing organization selects and tests products according to SELLERSMAYAPPLY and RANDOMTESTING mechanisms.

We first make the following definition to simplify our introduction of the mechanisms.[54]

Definition 1 ((Non-)Dominated products)**.** *Let $\emptyset \neq Z \subseteq F$ be a non-empty set of sellers. A seller $f_t \in Z$ offers a* **dominated** *product in Z if $\exists f_j \in Z$ with $\Big(\big(p_j \leqslant p_t\big) \wedge \big(q_j > q_t\big)\Big) \vee \Big(\big(p_j < p_t\big) \wedge \big(q_j \geqslant q_t\big)\Big)$. A seller $f_t \in Z$ offers a* **non-dominated** *product in Z if $\forall f_j \in Z$*

- *if $p_j < p_t$, then $q_j < q_t$,*
- *if $q_j > q_t$, then $p_j > p_t$.*

When referring to a true submarket of F, i.e., if $Z \subset F$, we call a product **locally** *(non-) dominated. When referring to the whole market F, i.e., if $Z = F$, we call a product* **globally** *(non-) dominated.*

Essentially, a product is dominated in a set (or market) if at least one seller in this set offers a strictly higher product quality without being more expensive, or a strictly lower price without offering a lower product quality. By comparison, a product model is non-dominated in a set if every seller in this set offering a strictly higher product quality also has a strictly higher price, and every seller offering a strictly lower price also offers a strictly lower quality. Note that, in the following, we use the terms "seller with (non-) dominated product" and "(non-)dominated seller" equivalently.

[54] This definition is adapted from Vollstaedt et al. (2020).

To illustrate definition 1, consider the following local market: $Z = \{f_1, f_2, f_4, f_5, f_6\}$, with
$q_1 = 2, p_1 = 5,$
$q_2 = 3, p_2 = 10,$
$q_4 = 1, p_4 = 11,$
$q_5 = 2, p_5 = 9,$
$q_6 = 3, p_6 = 28.$
Furthermore, consider the following global market: $F = Z \cup f_3$, with $q_3 = 3$ and $p_3 = 9.5$. While sellers f_1 and f_2 are locally non-dominated in market Z, sellers f_1 and f_3 are globally non-dominated in market F.

Now we introduce our proposed mechanism SELLERSMAYAPPLY and the random selection mechanism RANDOMTESTING respectively.

Our proposed mechanism SELLERSMAYAPPLY Under our proposed mechanism, sellers are able to influence whether a testing organization will test their product model. The mechanism consists of 4 steps.

- STEP 0: After seeing the prices and qualities of all sellers, each seller independently decides whether to apply to have her product tested by the testing organization. If a seller applies, she needs to report the quality of her product to the testing organization (reporting a false quality is allowed). Each applicant pays an application deposit μ to the testing organization.
- STEP 1: Among the set of applicants (denoted as F_0), select products which satisfy the following criteria:
  - The reported quality is not 1 (i.e., the reported quality is either 2 or 3).
  - It is locally non-dominated among applicants based on each applicant's reported quality (or updated quality, if available).
  - It has not been tested in the previous iteration (if any).

  Denote the set of these selected products as F_1. The testing organization returns the application deposits $\mu > 0$ to all sellers whose products are in F_1.

- STEP 2: Among F_1, if there exist identical products (same reported quality and same price), randomly select one product among them. Denote the set of selected products as F_2 (there should be at most 2 products in F_2).

- STEP 3:

  - Test all untested products in F_2 and reveal the quality of all products with a true quality statement. Do not reveal the quality of a product with a false quality statement.

  - The seller f_i who is found out to report a false quality, if any, pays a lying fee of $\sigma_i > 0$. To ensure that the lying fee is large enough to deter a false reported quality, we consider a dynamic lying fee which depends on the seller's ex-post revenue and is paid after the transaction is completed. f_i needs to pay a lying fee that is strictly greater than her ex-post revenue. In other words, $\sigma_i = p_i d_i + \underline{\sigma}$, where $\underline{\sigma}$ is a constant strictly greater than 0.

  - If no false quality reporting is detected or if all applicants' products have been tested or all testing capacity has been used up, then finish the algorithm. Otherwise, update F_0 based on tested sellers' true quality and return to Step 1.

The RANDOMTESTING mechanism Under the RANDOMTESTING mechanism, sellers cannot directly influence whether the testing organization will test their products. The testing organization randomly selects $k = 2$ sellers' products from F and reveal their qualities to buyers.

3.2.1.5. Procedures of a Market Transaction

A market transaction happens with the following stages:

- STAGE 1: n sellers determine quality and price simultaneously.

- STAGE 2: The product mechanism (SELLERSMAYAPPLY or RANDOMTESTING) is implemented.

- STAGE 3: All buyers see each seller's price as well as the qualities of products revealed by the testing organization. Each buyer decides from whom to purchase a product or buys nothing.

3.2.2. Theoretical Predictions

3.2.2.1. When Each Buyer's Surplus is Maximized

Having established the market settings in the previous subsection, we now analyze the market with different product testing mechanisms.

Since we consider a one-shot transaction, no seller should have the incentive to charge a price lower than her unit cost. Therefore, we know from (84) and (85) that a buyer with $\theta = \theta_L$ will maximize her surplus when she purchases a product with $q = 2$ and $p = c(2)$, while a buyer with $\theta = \theta_H$ will maximize her surplus when she purchases a product with $q = 3$ and $p = c(3)$.

3.2.2.2 SELLERSMAYAPPLY Mechanism

In this subsection, we analyze a world with incomplete information about product quality where a testing organization uses the SELLERSMAYAPPLY mechanism to select at most $k = 2$ products to test.

Since buyers have incomplete information about product quality, they will form a belief about the expected quality of a product given its price. More precisely, each buyer will have a subjective quality distribution function for each product whose quality is not revealed given the price of the product (hereafter, unrevealed product). We assume that all buyers have the same subjective quality distribution function and this function is common knowledge.

We make the following assumptions about sellers' and buyers' in some tie-breaking or trivial situations. We assume that all these assumptions are also common knowledge among all sellers and buyers.

Assumption 1 (A1) (Sequential Rationality). *Every player is sequentially rational.*

Assumption 2 (A2) (Zero probability on "unrationalizable" quality levels). *In a buyers' subjective quality distribution for an unrevealed seller, all quality levels which violate A1 or any corollary that can be derived from A1, A2, A3.1, A3.2, A4 and/or A5 will have a 0 probability.*

Assumption 3.1 (A3.1) ("Unraveling quality uncertainty" seller tie-breaking rule). *Given all n sellers' price and quality bundles and all the other $n-1$ sellers' application decisions, if a* *seller's application decision does not make a difference in her expected quality and her expected payoff, then she chooses to apply to unravel uncertainty about her quality.*

Assumption 3.2 (A3.2) ("Quality-caring" seller tie-breaking rule). *Given all n sellers' price and quality bundles and all the other $(n-1)$ sellers' application decisions, if a seller is indifferent between applying and not applying, she will choose the one that gives her a higher expected quality.*

Assumption 4 (A4) (Not buying from any seller when the maximum expected profit is 0). *When the maximum expected payoff from buying from any seller is 0, then the buyer will choose not buying.*

Assumption 5 (A5) (Non-negative markup). *No seller will set her price to be lower than the marginal cost.*

We make A3.1 based on ambiguity aversion. A3.2 is made based on the assumption that sellers want buyers to believe/observe that their products have a higher quality, even if a product with a higher quality does not increase their monetary payoffs. We assume A5, because sellers usually charge a price lower than the marginal cost for the purpose of predatory pricing. In this study, we do not discuss the possibility of predatory pricing, because we focus on an one-shot interaction.

Our goal is to find all Perfect Bayesian Equilibria in this game, so we use the backward induction method. It is common knowledge that each buyer will maximize her expected payoff based on the subjective quality distribution function for an revealed seller given the seller's price. Since each seller is rational, she should be able to form a correct belief about the buyer's subjective quality distribution function. Then she uses this function to determine whether to apply for quality testing or not in Stage 2, given all n sellers' qualities and prices in Stage 1.

We first show that applying with a false reported quality is a dominated strategy for a seller.

Corollary 0 (C0). *Applying for quality testing with a false reported quality is a dominated strategy for any seller $f_i \in F$.*

With C0, we only need to consider whether each seller will choose applying with a true reported quality or not applying. We derive the following corollaries about each seller's application decision in Stage 2 given her quality and price in Stage 1, based on the common knowledge about A1, A2, A3.1, A3.2, A4 and A5.

Corollary 1 (C1). *A seller with $q = 1$ will not apply.*

Corollary 2.1 (C2.1). *A globally non-dominated seller with $q = 3$ must apply with a true reported quality.*

Corollary 2.2 (C2.2). *A globally dominated seller with $q = 3$ will not apply.*

Corollary 3.1 (C3.1). *A globally non-dominated seller with $q = 2$ must apply with a true reported quality.*

Corollary 3.2 (C3.2). *A globally dominated seller with $q = 2$ will not apply.*

The proofs for these corollaries can be found in appendix .

Based on the C1, C2.1, C2.2, C3.1, C3.2 and A2, we can derive the buyer's subjective belief about an unrevealed seller's quality distribution:

Corollary 4.1 (C4.1). *The buyer's subjective belief about an unrevealed seller f_t's quality distribution is:*

- ***Case 1:*** *If there are two revealed sellers (i.e., one with $q = 2$, denoted as $f^2_{K'}$ and the other with $q = 3$, denoted as $f^3_{K'}$), and there must be $p^3_{K'} > p^2_{K'}$:*

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^3_{K'}$	α_1	β_1	$1 - \alpha_1 - \beta_1$
if $p^2_{K'} \leqslant p_t < p^3_{K'}$	α_2	$1 - \alpha_2$	*0*
if $p_t < p^2_{K'}$	*1*	*0*	*0*

- ***Case 2:*** *If there is only one revealed seller, and she has $q = 2$, denoted as $p^2_{K'}$:*

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^2_{K'}$	α_3	$1 - \alpha_3$	*0*
if $p_t < p^2_{K'}$	*1*	*0*	*0*

- ***Case 3:*** *If there is only one revealed seller, and she has $q = 3$, denoted as $p^3_{K'}$:*

	$Pr(q=1)$	$Pr(q=2)$	$Pr(q=3)$
if $p_t \geqslant p^3_{K'}$	α_4	β_2	$1-\alpha_4-\beta_2$
if $p_t < p^3_{K'}$	*1*	*0*	*0*

- ***Case 4:*** *If there is no revealed seller, then:*

$Pr(q=1)$	$Pr(q=2)$	$Pr(q=3)$
1	*0*	*0*

where $\alpha_1, \beta_1, (1-\alpha_1-\beta_1), \alpha_2, \alpha_3, \alpha_4, \beta_2 \in [0,1]$

Based on the quality distribution above, we can derive the expected quality of an unrevealed seller's product:

Corollary 4.2 (C4.2). *The buyer's belief about an unrevealed seller f_t's expected quality is:*

- ***C4.2.1*** *If there are two revealed sellers (i.e., one with $q = 2$, denoted as $f^2_{K'}$ and the other with $q = 3$, denoted as $f^3_{K'}$), and there must be $p^3_{K'} > p^2_{K'}$:*

$$E_{f_t \notin K'}(q_t) = \begin{cases} 3 - 2\alpha_1 - \beta_1 & if\ p_t \geqslant p^3_{K'} \\ 2 - \alpha_2 & if\ p^2_{K'} \leqslant p_t < p^3_{K'} \\ 1 & if\ p_t < p^2_{K'} \end{cases}$$

- ***C4.2.2*** *If there is only one revealed seller, and she has $q = 2$, denoted as $p^2_{K'}$:*

$$E_{f_t \notin K'}(q_t) = \begin{cases} 2 - \alpha_3 & if\ p_t \geqslant p^2_{K'} \\ 1 & if\ p_t < p^2_{K'} \end{cases}$$

- ***C4.2.3*** *If there is only one revealed seller, and she has $q = 3$, denoted as $p^3_{K'}$:*

$$E_{f_t \notin K'}(q_t) = \begin{cases} 3 - 2\alpha_4 - \beta_2 & if\ p_t \geqslant p^3_{K'} \\ 1 & if\ p_t < p^3_{K'} \end{cases}$$

- ***C4.2.4*** *If there is no revealed seller, then:*

$$E_{f_t \notin K'}(q_t) = 1$$

where $\alpha_1, \beta_1, (1-\alpha_1-\beta_1), \alpha_2, \alpha_3, \alpha_4, \beta_2 \in [0,1]$.

With all the assumptions and corollaries above, we find that all pure-strategy profiles to be weak Perfect Bayesian Equilibria have the following features.

Proposition 3. *In the SellersMayApply condition, the only pure-strategy profiles to be weak Perfect Bayesian Equilibria must have the following features:*

- γ_2 *sellers play* $(q=2, p=c(2), Apply, Report\ q=2)$, *with* $\gamma_2 \geqslant 2$;
- γ_3 *sellers play* $(q=3, p=c(3), Apply, Report\ q=3)$, *with* $\gamma_3 \geqslant 2$;
- γ_1 *sellers play* $(q=1, p=c(2), Not\ Apply)$, *with* $\gamma_1 \geqslant 1$;
- $(n-\gamma_1-\gamma_2-\gamma_3)$ *sellers play* $(q=1, p=c(3), Not\ Apply)$, *with* $\gamma_1+\gamma_2+\gamma_3 < n$.
- *Buyers' belief about the quality distribution of an unrevealed seller* f_t *given her price* p_t:
  - *If there are two revealed sellers (i.e., one with* $q=2$, *denoted as* $f_{K'}^2$ *and the other with* $q=3$, *denoted as* $f_{K'}^3$*), and there must be* $p_{K'}^3 > p_{K'}^2$:

	$Pr(q=1)$	$Pr(q=2)$	$Pr(q=3)$
if $p_t \geqslant p_{K'}^3$	$\frac{\gamma_1}{\gamma_1+\gamma_2-1}$	*0*	$1-\frac{\gamma_1}{\gamma_1+\gamma_2-1}$
if $p_{K'}^2 \leqslant p_t < p_{K'}^3$	$\frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	$1-\frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	*0*
if $p_t < p_{K'}^2$	*1*	*0*	*0*

  - *If there is only one revealed seller, and she has* $q=2$, *denoted as* $p_{K'}^2$ $(\alpha_3 > 0)$:

	$Pr(q=1)$	$Pr(q=2)$	$Pr(q=3)$
if $p_t \geqslant p_{K'}^2$	α_3	$1-\alpha_3$	*0*
if $p_t < p_{K'}^2$	*1*	*0*	*0*

  - *If there is only one revealed seller, and she has* $q=3$, *denoted as* $p_{K'}^3$ $(\alpha_4+\beta_2 > 0)$:

	$Pr(q=1)$	$Pr(q=2)$	$Pr(q=3)$
if $p_t \geqslant p_{K'}^3$	α_4	β_2	$1-\alpha_4-\beta_2$
if $p_t < p_{K'}^3$	*1*	*0*	*0*

– *If there is no revealed seller, then:*

$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
1	*0*	*0*

where $\alpha_3 > 0$ *and* $\alpha_4 + \beta_2 > 0$.

- *Each buyer with* $\theta = \theta_L$ *will buy a product from the revealed seller with* $q = 2$ *and* $p = c(2)$.
- *Each buyer with* $\theta = \theta_H$ *will buy a product from the revealed seller with* $q = 3$ *and* $p = c(3)$.

Proof. To prove this proposition, we first prove some lemmas (i.e., L0.1 through L7). We prove the lemmas and this proposition in appendix . □

Since each buyer with $\theta = \theta_L$ will buy a product with $q = 2$ and $p = c(2)$ and each buyer with $\theta = \theta_H$ will buy a product with $q = 3$ and $p = c(3)$, each buyer's payoff is maximized. Therefore, we maximize consumer surplus when using our proposed product testing mechanism, and this mechanism must (weakly) dominate any other alternative mechanism.

3.2.2.3. RANDOMTESTING Mechanism

When analyzing the RANDOMTESTING mechanism, we use all applicable assumptions from the SELLERSMAYAPPLY mechanism. Since each seller cannot directly affect whether and with what probability she will be tested, A3.1 ("Unraveling quality uncertainty" seller tie-breaking rule) and A3.2 ("Quality-caring" seller tie-breaking rule) are not applicable under RANDOMTESTING. Thus, only assumptions A1 (Sequential rationality), A2 (Zero probability on "unrationalizable" quality levels), A4 (Not buying from any seller when the maximum expected profit is 0), and A5 (Non-negative markup) are relevant.

We prove that, under RANDOMTESTING, there does not exist any Perfect Bayesian Equilibrium that can achieve the same buyer surplus as under SELLERSMAYAPPLY or under COMPLETEINFORMATION.

Proposition 4. *Under* RANDOMTESTING*, there does not exist any Perfect Bayesian Equilibrium, if any, that can yield the same buyer surplus as under* SELLERSMAYAPPLY.

The proof can be found in appendix . Therefore, the SELLERSMAYAPPLY mechanism must strictly dominate the RANDOMTESTING mechanism.

3.3. Experimental Design and Hypotheses

Based on the theoretical framework introduced in the previous section, we design a laboratory experiment to test our theoretical predictions and ascertain the extent to which these predictions are observed with human decision makers. We design two experimental conditions: SELLERSMAYAPPLY and RANDOMTESTING according to Section 3.2.

In our experiment, we use a between-subject design, and we conduct three sessions per condition. Each session consists of 20 rounds. At the end of a session, one of the 20 rounds is chosen randomly for payment (2 ECU = US $ 1). In each session, we include 6 sellers ($n = 6$), 6 buyers ($s = 6$), and one testing organization. While sellers and buyers are played by actual participants, the testing organization is simulated by the computer. Player roles, i.e., seller or buyer, are assigned randomly at the beginning of a session and remain constant afterwards. Player IDs, i.e., seller 1, 2 or 3 etc., are re-shuffled, i.e., they are assigned randomly at the beginning of each round. The testing organization selects at most two products to be tested ($k = 2$).

In each round, sellers choose one of three quality levels, i.e., $q_t \in \{1, 2, 3\}$. As to their cost function, we implement one of the simplest ones fulfilling $c'(q_t) > 0$ and $c''(q_t) > 0$, namely quadratic unit costs, i.e., $c(q_t) = q_t^2$. As to buyers' valuations of quality, θ_L takes the value of 4, and θ_H takes the value of 8, such that θ_L, θ_H , and $c(q_t)$ satisfy (84) and (85). In each round, there are three buyers with θ_L, and three buyers with θ_H. While buyers are neither informed of the cost function nor of the quality distribution, they are, at the beginning of a session, informed that, if all products are offered at marginal costs, quality level 2 (3) would be optimal for buyers with $\theta = 4$ ($\theta = 8$). Buyers learn a product's quality only if the testing organization has revealed it, or after having purchased a product. If applicable, sellers incur an application deposit μ of 0.1 ECU and a lying fee σ of 10 ECU+revenue if a false quality report is detected.

To avoid bankruptcy, we pay each subject an initial endowment of 38 ECU (16 ECU as a show-up fee + 22 ECU for answering the comprehension questions). Each subject also receives 2 ECU for answering questions about their beliefs regarding the expected quality of untested products in Round 20, i.e., in the last round. We elicit first-order beliefs for buyers and second-order beliefs for sellers. All beliefs are elicited after subjects make their decisions in Round 20, but before they receive feedback on their payoff. Table 3.1 summarizes the procedures in each experiment session.

Table 3.1. Procedures of the experiment

Experimental instructions Comprehension questions
Product testing game (round 1 to 19): - Decision making - Round feedback Product testing game (round 20): - Decision making - Belief elicitation - Round feedback
Demographic questionnaire Final payoff feedback

We base our hypothesis on our theoretical results from Propositions 1 and 2.

Hypothesis: A buyer's surplus in the SELLERSMAYAPPLY condition is higher than that in the RANDOMTESTING condition.

Our experiment was comprised of 10 sessions (5 per condition) and was conducted in-person between October 2022 and February 2023 at the Behavioral Laboratory at the University of Michigan. In total, 120 subjects participated in the experiment. On average, a session lasted 90 minutes, and a subject earned $22.30. More details on the number of subjects are displayed in Table 3.2. Subjects were invited to participate in the experiment using ORSEE (Greiner, 2015). The experiment was programmed and conducted with zTree (Fischbacher, 2007). Experimental instructions and main decision screens can be found in Appendix 3.B.

Table 3.2. Number of sellers and buyers per session, and number of sessions and subjects per condition

Condition	Sellers per session	Buyers per session	Sessions	Subjects per condition
SELLERSMAYAPPLY	6	6	5	60
RANDOMTESTING	6	6	5	60
Total			10	120

Table 3.3. Effect of the SELLERSMAYAPPLY mechanism on buyer surplus (Random-effects Linear Regression)

	Buyer's surplus
SellersMayApply	3.027***
	(0.514)
Constant	5.703***
	(0.499)
Observations	1,200

Note: (1) Standard errors are clustered at the session level. (2) *** p<0.01, ** p<0.05, * p<0.1.

3.4. Results

In this section, we demonstrate our experimental results and test our hypothesis.

As Table 3.3 shows, we find that a buyer's surplus in the SELLERSMAYAPPLY condition is higher than that in the RANDOMTESTING condition by 3.027 ECUs on average, and this difference is statistically significant ($p < 0.01$). This result supports our hypothesis.

Result: A buyer's surplus in the SELLERSMAYAPPLY condition is significantly higher than that in the RANDOMTESTING condition.

Figure 3.1 demonstrates the average buyer surplus in each round in two conditions. We see that the average buyer surplus in the SELLERSMAYAPPLY condition in each round is higher than that in the RANDOMTESTING condition.

To better understand how the SELLERSMAYAPPLY mechanism improves buyer surplus relative to the RANDOMTESTING mechanism, we plot all 6 sellers' products in the last round (i.e., Round 20) of each session in Figure 3.2. The four graphs on the left column demonstrate the distribution of six sellers' products in each session of the SELLERSMAYAPPLY condition, while the four graphs on the right column show the distribution of six sellers' products in each session of the RANDOMTESTING condition. The three dashed horizontal lines on each graph indicate the unit costs of products with qualities 1, 2 and 3.

From Figure 3.2, We can see that there are mainly two reasons why the SELLERSMAYAPPLY mechanism improves buyer surplus. First, in all three SELLERSMAYAPPLY sessions, there are always sellers who offer products that can close to $(q = 2, p = 4)$ and $(q = 3, p = 9)$, which max-

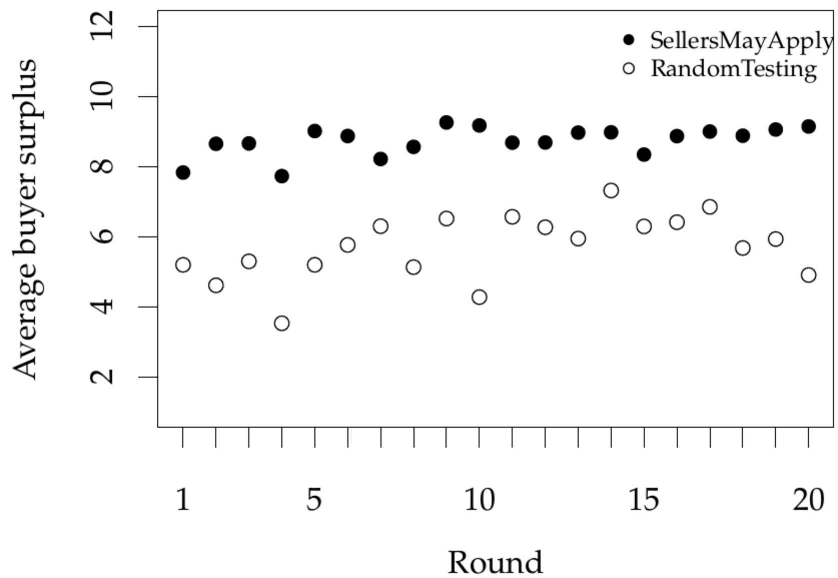


Figure 3.1. Buyer surplus over time

imize $\theta = \theta_L$ and $\theta = \theta_H$ buyers' surplus respectively. In the three RANDOMTESTING sessions, sellers' provision of products tend to deviate more from the optimal quality-price bundles. Second, the testing organization is always able to reveal globally non-dominated products to buyers when using the SELLERSMAYAPPLY mechanism. Knowing how the SELLERSMAYAPPLY mechanism select and test products, buyers almost always buy products revealed by the testing organization. In the RANDOMTESTING condition, which two products are tested is random, so buyers sometimes choose to purchase an unrevealed product. Many of the revealed products yield low surplus to buyers.

3.5. Discussion and Conclusion

In this paper, we discuss markets in which the vertical dimensions of product characteristics, i.e., vertical quality, is not visible to consumers unless it is revealed by an independent testing organization. We investigate whether the testing organization can make full use of its limited testing capacity to test and reveal the qualities of products that maximize consumer surplus through our proposed product testing mechanism SELLERSMAYAPPLY. We prove that in the product testing game where the testing organization uses the SELLERSMAYAPPLY mechanism, all pure-strategy weak Perfect Bayesian Equilibria maximize consumer surplus, so that the

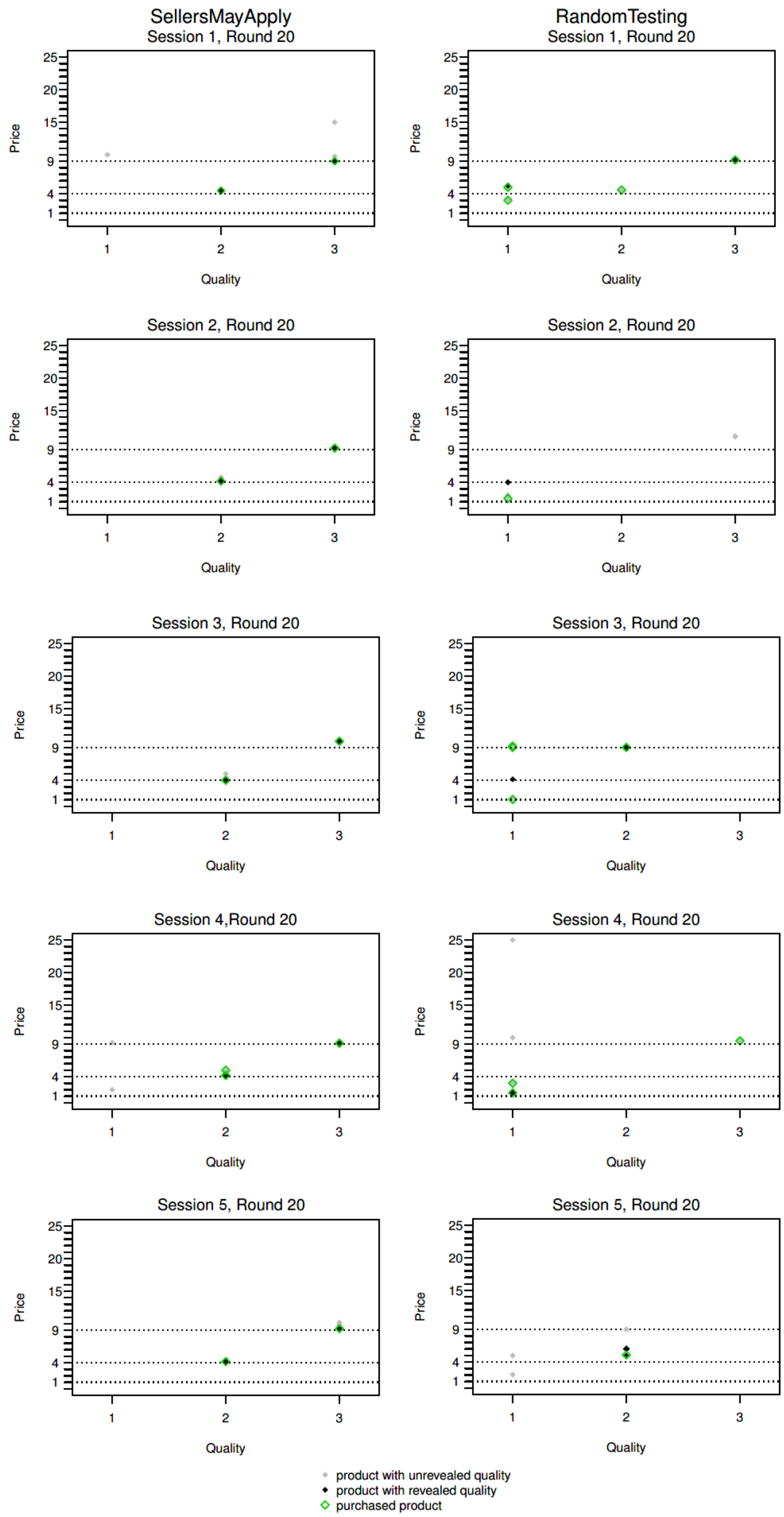


Figure 3.2. Product distribution in the last round of each session

SELLERSMAYAPPLY mechanism theoretically (weakly) dominates any other alternative product testing mechanism. We also discuss a generic testing mechanism, RANDOMTESTING, which randomly test products within the testing capacity of the testing organization. We show that under the RANDOMTESTING mechanism, there does not exist a (weak) perfect Bayesian Equilibrium that maximizes consumer surplus.

The results from our laboratory experiment support our prediction that consumer surplus is significantly higher under SELLERSMAYAPPLY compared to RANDOMTESTING.

Our theoretical and experimental results demonstrate that our proposed product testing mechanism increases consumer surplus through two channels. First, the mechanism incentivizes enough sellers to produce products with qualities that are preferred by consumers and with prices close to or equal to the unit cost. Second, the mechanism enables sellers to influence the product testing outcomes and ensures that only the qualities of globally non-dominated products will be revealed to consumers. Overall, our study shows that we can improve consumer surplus in a market with information asymmetry through a product testing mechanism which only tests and reveals the qualities of a small fraction of products on the market.

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Appendices

3.A. Proofs of Corollaries, Lemmas and Propositions

Corollary 0 (C0). *Applying for quality testing with a false reported quality is a strictly dominated strategy for any seller $f_i \in F$.*

Proof. Consider the perspective of seller f_i, holding all the other $n-1$ sellers' qualities, prices and application decisions constant. We distinguish the following two cases.

Case 1 Seller f_i would not be selected into F_1 if she applied with a false reported quality.

- **Case 1.1** If f_i applied with a false reported quality in Case 1, she would pay the application deposit μ which would not be returned to her.
- **Case 1.2** If f_i did not apply in Case 1, her expected quality would be the same as that in Case 1.1, because holding all n sellers' price and quality bundles and all the other $n-1$ sellers' application decisions constant, her decision of not applying would not make any difference in terms of the outcome buyers could see (i.e., the revealed qualities and which sellers were tested and which sellers not) compared with Case 1.1. However, she would not pay the application deposit.
- Therefore, not applying strictly dominates applying with a false reported quality for seller f_i in Case 1.

Case 2 Seller f_i would be selected into F_1 if she applied with a false reported quality.

- **Case 2.1** With a probability of 1, seller f_i would be selected into F_2 (i.e., would be tested) if she applied with a false reported quality.
  - **Case 2.1.1** If f_i applied with a false reported quality, f_i would need to pay σ_i. Since σ_i is greater than her ex-post revenue, f_i's payoff would be strictly negative.
  - **Case 2.1.2** If f_i did not apply, her expected payoff would be non-negative according to A5.
  - Therefore, not applying strictly dominates applying with a false reported quality for seller f_i in Case 2.1.

- **Case 2.2** With a probability of λ, with $\lambda \in (0, 1)$, seller f_i would be selected into F_2 (i.e., would be tested) if she applied with a false reported quality in Case 2.
  - **Case 2.2.1** If f_i applied with a false reported quality, we can furthermore distinguish the following two cases.
    * **Case 2.2.1.1** (With probability λ) If f_i ended up in F_2 (i.e., were tested), she would need to pay σ_i. Since σ_i is greater than her ex-post revenue, f_i's payoff must be strictly negative. Denote this negative (expected) payoff as π^{tested}, with $\pi^{tested} < 0$.
    * **Case 2.2.1.2** (With probability $1 - \lambda$) If f_i did not end up in F_2 (i.e., were not tested), but were in F_1, f_i would be returned the application deposit μ. There could be one or multiple testing outcomes (i.e., which seller(s)' is (are) tested and revealed), denoted as $o_1, \ldots, o_\xi$. Denote f_i's ex-post payoff in o_t as π_{o_t} ($t = 1, \ldots, \xi$). Denote the probability of the occurrence of o_t as λ_{o_t}. According to A5, it follows that $\pi_{o_t} \geqslant 0$, with $t = 1, \ldots, \xi$. Therefore, f_i's expected payoff is $\sum_{t=1}^{\xi} \pi_{o_t} \lambda_{o_t} \geqslant 0$ (with $\sum_{t=1}^{\xi} \lambda_{o_t} = 1 - \lambda$).
    * Therefore, f_i's expected payoff when applying is $\lambda \pi^{tested} + \sum_{t=1}^{\xi} \pi_{o_t} \lambda_{o_t}$.
  - **Case 2.2.2** If f_i did not apply:
    * **Case 2.2.2.1** When f_i does not apply, each of the possible outcomes in Case 3.1.2, o_t $(t = 1, \ldots, \xi)$ will still happen with a positive probability. Denote the probability of the occurrence of o_t in Case 3.2.1 as $\lambda^{'}_{o_t}$. Since f_i does not apply, the testing slot will be equally or less congested, so there must be $\lambda^{'}_{o_t} \geqslant \lambda_{o_t}$, with $t = 1, \ldots, \xi$. f_i's expected payoff is $\sum_{t=1}^{\xi} \pi_{o_t} \lambda^{'}_{o_t} \geqslant 0$, and there must be $\sum_{t=1}^{\xi} \pi_{o_t} \lambda^{'}_{o_t} \geqslant \sum_{t=1}^{\xi} \pi_{o_t} \lambda_{o_t}$.
    * **Case 2.2.2.2** In addition to Case 3.2.1, it is also possible (with a probability $1 - \sum_{t=1}^{\xi} \lambda^{'}_{o_t}$) that with f_i's quitting, there are new sellers selected into the F_1 compared with Case 3.2.1. In other words, there could be new testing outcome(s) that would not happen in Case 3.2.1. According to A5, it follows that f_i's ex-post payoff in each of these new testing outcomes (if any) must be non-negative. Therefore, f_i's (expected) payoff, denoted as $\pi^{untested}$, must be

non-negative (i.e., $\pi^{**} \geqslant 0$).

    * Therefore, f_i's expected payoff when not applying is $\sum_{t=1}^{\xi} \pi_{o_t}\lambda_{o_t}^{'} + (1 - \sum_{t=1}^{\xi} \lambda_{o_t}^{'})\pi^{**}$.

  – With $\sum_{t=1}^{\xi} \pi_{o_t}\lambda_{o_t}^{'} \geqslant \sum_{t=1}^{\xi} \pi_{o_t}\lambda_{o_t}$, $\pi^{*} < 0$ and $\pi^{**} \geqslant 0$, we can conclude that $\lambda\pi^{*} + \sum_{t=1}^{\xi} \pi_{o_t}\lambda_{o_t} < \sum_{t=1}^{\xi} \pi_{o_t}\lambda_{o_t}^{'} + (1 - \sum_{t=1}^{\xi} \lambda_{o_t}^{'})\pi^{**}$. Therefore, not applying strictly dominates applying with a false reported quality for seller f_i in Case 2.2.

- Therefore, not applying strictly dominates applying with a false reported quality for seller f_i in Case 2.

Therefore, applying for quality testing with a false reported quality is a strictly dominated strategy for any seller $f_i \in F$. □

Corollary 1 (C1). *A seller with $q = 1$ will not apply.*

Proof. When there exist(s) seller(s) with $q = 1$, denote one of them as f_1. Consider f_1's best response without loss of generality.

- **Case 1:** If f_1 applies (with a true reported quality, hereafter), she will not be selected to be tested, so she will pay the application deposit μ which will not be returned to her.

- **Case 2:** If f_1 does not apply, her expected quality will be the same as that in Case 1, because holding all n sellers' price and quality bundles and all the other 5 sellers' application decisions constant, her decision of not applying will not make any difference in terms of the outcome buyers can see (i.e., the revealed qualities and which sellers are tested and which sellers are not) compared with Case 1. However, she does not pay the application deposit μ.

- Therefore, not applying is a best response for f_1. According to A1, f_1 will not apply, and it is common knowledge.

- If there are multiple sellers with $q = 1$, each of them will not apply either, using the same reasoning as we used for f_1.

□

Corollary 2.1 (C2.1). *A globally non-dominated seller with* $q = 3$ *must apply with a true reported quality.*

Proof. Let's discuss different cases.

- **Case 1:** Suppose there is only one globally non-dominated sellers with $q = 3$. Denote her as f_{ND_3}. Consider f_{ND_3}'s best response.
  - **Case 1.1:** If f_{ND_3} applies, then she must be selected to be tested, so her quality is revealed to be 3.
  - **Case 1.2:** If f_{ND_3} does not apply, then her expected quality can be 3 or smaller than 3.
    - **Case 1.2.1:** If her expected quality is 3, then according to A3.1, she will choose to apply to unravel uncertainty about her quality (her expected payoff from applying and not applying should also be the same since her application deposit must be returned to her).
    - **Case 1.2.2:** If her expected quality is smaller than 3, then applying will bring her a higher expected quality. If this higher expected quality raises her expected profit (which in turn raises her expected profit), then applying is a best response. If this higher expected quality does not change her expected profit, applying is still a (weakly) best response, and according to A3.2, she chooses applying.
  - Therefore, f_{ND_3} will apply, and it is common knowledge.
- **Case 2:** Suppose there are m $(2 \leqslant m \leqslant n)$ identical globally non-dominated sellers with $q = 3$. Denote one globally non-dominated seller with $q = 3$ as $f_{ND_3^1}$ and the other globally non-dominated sellers with $q = 3$ as $f_{ND_3^2}, \ldots, f_{ND_3^m}$. Consider $f_{ND_3^1}$'s best response without loss of generality.
  - **Case 2.1:** Suppose there are α sellers among $f_{ND_3^2}, \ldots, f_{ND_3^m}$ who apply $(\alpha > 0)$:
    - **Case 2.1.1:** If $f_{ND_3^1}$ applies, then:
      - **Case 2.1.1.1:** With $\frac{1}{\alpha+1}$ probability, $f_{ND_3^1}$ will be randomly selected to be tested, and then her quality is revealed to be 3.

- Case 2.1.1.2: With $\frac{\alpha}{\alpha+1}$ probability, $f_{ND_3^1}$ will not be randomly selected, and then her expected quality must satisfy $E(q) \leqslant 3$. Her application deposit σ will be returned to her, because she is also globally non-dominated with $q = 3$.

  * **Case 2.1.2:** If $f_{ND_3^1}$ does not apply, then there must be one seller among $f_{ND_3^2}, \ldots,$ $f_{ND_3^m}$ who is selected to be tested, and $f_{ND_3^1}$'s expected quality will be the same as that in Case 2.1.1.2. This is because holding all n sellers' price and quality bundles and all the other 5 sellers' application decisions constant, her decision of not applying will not make any difference in terms of the outcome buyers can see (i.e., the revealed qualities and which sellers are tested and which sellers are not) compared with Case 2.1.1.2.
  * Therefore, $f_{ND_3^1}$'s expected quality from applying must be higher than or equal to that from not applying. Using the same reasoning as we do in Case 1.2, $f_{ND_3^1}$ will apply.

- **Case 2.2:** Suppose there is no seller among $f_{ND_3^2}, \ldots, f_{ND_3^m}$ who applies:
  * **Case 2.2.1:** If $f_{ND_3^1}$ applies, then her quality is revealed to be 3.
  * **Case 2.2.2:** If $f_{ND_3^1}$ does not apply, then her expected quality must satisfy $E(q) \leqslant$ 3.
  * Therefore, using the same reasoning as we do in Case 1.2, $f_{ND_3^1}$ will apply.
- Based on the conclusions from Case 2.1 and Case 2.2, $f_{ND_3^1}$ will apply, and it is common knowledge, according to A1.
- Since $f_{ND_3^1}, \ldots, f_{ND_3^m}$ are identical sellers, they face the same situation, so all globally non-dominated sellers with $q = 3$ will apply.

□

Corollary 2.2 (C2.2). *A globally dominated seller with $q = 3$ will not apply.*

Proof. Denote (one of) the globally dominated seller(s) with $q = 3$ as f_{D_3}. Consider f_{D_3}'s best response. Let's discuss different cases.

- **Case 1:** If she applies, since she knows that globally non-dominated sellers with $q = 3$ must apply according to C2.1 and C2.2, she will not be selected to be tested. She needs to pay the application deposit σ which will not be returned to her.

- **Case 2:** If she does not apply, then her expected quality would be the same as that in Case 1, because holding all n sellers' price and quality bundles and all the other 5 sellers' application decisions constant, her decision of not applying will not make any difference in terms of the outcome buyers can see (i.e., the revealed qualities and which sellers are tested and which sellers are not) compared with Case 1. However, she does not pay the application deposit σ.
- Therefore, not applying is a best response for f_{D_3}. According to A1, f_{D_3} will not apply, and it is common knowledge.
- If there are multiple globally dominated sellers with $q = 3$, each of them will not apply either, using the same reasoning as we used for f_{D_3}.

□

Corollary 3.1 (C3.1). *A globally non-dominated seller with $q = 2$ must apply with a true reported quality.*

Proof. Let's discuss different cases.

- **Case 1:** In addition to sellers with $q = 2$, there also exist sellers with $q = 3$:
  - **Case 1.1:** Suppose there is only one globally non-dominated sellers with $q = 2$. Denote her as f_{ND_2}. Since she is globally non-dominated, we must have $p_{ND_2} < p_{ND_3}$. Consider f_{ND_2}'s best response.
    * **Case 1.1.1:** If f_{ND_2} applies, then she must be selected to be tested, so her quality is revealed to be 2.
    * **Case 1.1.2:** If f_{ND_2} does not apply, since $p_{ND_2} < p_{ND_3}$ buyers will conclude that f_{ND_2} cannot have $q = 3$ based on C2.2 (which would make f_{ND_3} a globally dominated seller and would have a conflict with f_{ND_3} applying). Therefore, based on A2 and C2.2, f_{ND_2}'s expected quality must satisfy $1 \leqslant E(q) \leqslant 2$.

- **Case 1.1.2.1:** If f_{ND_2}'s expected quality is 2, then f_{ND_2} will apply according to A3.1 to unravel uncertainty about her quality (her expected payoff from applying and not applying should also be the same since her application deposit must be returned to her).
- **Case 1.1.2.2:** If f_{ND_2}'s expected quality is smaller than 2, then applying will bring her a high expected quality. If this higher expected quality raises her expected demand (which in turns raises her expected profit), then applying is a best response. If this higher expected quality does not change her expected profit, applying is still a (weakly) best response, and according to A3.2, she chooses applying.

* Therefore, f_{ND_2} will apply according to A1.

– **Case 1.2:** Suppose there are m $(m \geqslant 2)$ identical globally non-dominated sellers with $q = 2$ $(2 \leqslant m \leqslant n-1)$. Denote one globally non-dominated seller with $q = 2$ as $f_{ND_2^1}$ and the other globally non-dominated sellers with $q = 2$ as $f_{ND_2^2}, \ldots, f_{ND_2^m}$. Since they are globally non-dominated, we must have $p_{ND_2^i} < p_{ND_3}$ $(i = 1, \ldots, m)$. Consider $f_{ND_2^1}$'s best response without loss of generality.

* **Case 1.2.1:** Suppose there are α sellers among $f_{ND_2^2}, \ldots, f_{ND_2^m}$ who apply $(\alpha > 0)$. Using the a similar reasoning as that in C2.1 Case 2.1, it can be proved that $f_{ND_2^1}$ will apply.
* **Case 1.2.2:** Suppose there is no seller among $f_{ND_2^2}, \ldots, f_{ND_2^m}$ who applies. Using the a similar reasoning as that in C2.1 Case 2.2, it can be proved that $f_{ND_2^1}$ will apply.

– Based on the conclusions from Case 1.2.1 and Case 1.2.2, $f_{ND_2^1}$ must apply according to A1.

– Since $f_{ND_2^1}, \ldots, f_{ND_2^m}$ are identical sellers, they face the same situation, so all globally non-dominated sellers with $q = 2$ will apply.

• **Case 2:** In addition to sellers with $q = 2$, there do not exist sellers with $q = 3$:

– **Case 2.1:** Suppose there is only one globally non-dominated sellers with $q = 2$. Denote her as f_{ND_2}. Consider f_{ND_2}'s best response.

  * **Case 2.1.1:** If f_{ND_2} applies, then she must be selected to be tested, so her quality is revealed to be 2.
  * **Case 2.1.2:** If f_{ND_2} does not apply, then since there is no $q = 3$ seller, it is impossible for buyers to see a revealed $q = 3$ product. Buyers will conclude that f_{ND_2} cannot have $q = 3$ based on C2.1. Therefore, based on A2 and C2.2, f_{ND_2}'s expected quality must satisfy $1 \leqslant E(q) \leqslant 2$. Using the same reasoning as that in Case 1.1.2, it can be proved that f_{ND_2} will apply.

- **Case 2.2:** Suppose there are m $(m \geqslant 2)$ identical globally non-dominated sellers with $q = 2$ $(2 \leqslant m \leqslant n)$. Using a similar reasoning as that in Case 1.2, it can be proved that every globally non-dominated sellers with $q = 2$ will apply.

□

Corollary 3.2 (C3.2). *A globally dominated seller with* $q = 2$ *will not apply.*

Proof. Denote (one of) the globally dominated seller(s) with $q = 2$ as f_{D_2}. Let's discuss different cases.

- **Case 1:** In addition to sellers with $q = 2$, there also exist sellers with $q = 3$. In this case, there are two possible reasons that f_{D_2} is globally dominated:

  - **Case 1.1:** If there exists a globally non-dominated seller f_{ND_2} such that $p_{ND_2} < p_{D_2} < p_{ND_3}$.

    * **Case 1.1.1:** If she applies, she knows that f_{ND_2} must apply and she would not be selected. She needs to pay the application deposit which will not be returned to her.
    * **Case 1.1.2:** If she does not apply, then her expected quality would be the same as that in Case 1.1.1, because holding all n sellers' price and quality bundles and all the other 5 sellers' application decisions constant, her decision of not applying will not make any difference in terms of the outcome buyers can see compared with Case 1.1.1. However, she does not pay the application deposit.

- **Case 1.2:** If $p_{D_2} > p_{ND_3}$.
  * **Case 1.2.1:** If she applies, she knows that f_{D_2}, who globally dominates her, must apply and thus she would not be selected to be tested. She needs to pay the application deposit which will not be returned to her.
  * **Case 1.2.2:** If she does not apply, then using the same reasoning as that in Case 1.1.2, it can be proved that her expected quality would be the same as that in Case 1.2.1, but she does not pay the application deposit.
- Therefore, not applying is always a best response for f_{D_2}. According to A1, f_{D_2} will not apply.
- If there are multiple globally dominated sellers with $q = 2$, each of them will not apply either, using the same reasoning as we used for f_{D_2}.

- **Case 2:** In addition to sellers with $q = 2$, there do not exist sellers with $q = 3$. In this case, we use the same reasoning as that in Case 1.1, and it can be proved that f_{D_2} will not apply. If there are multiple globally dominated sellers with $q = 2$, each of them will not apply either.

□

Lemma 0.1 (L0.1). *If there exist sellers with $q = 2$ and $q = 3$ and (one of) the seller with the lowest price among $q = 2$, denoted as $f_{l_2^1}$, and (one of) the seller with the lowest price among $q = 3$, denoted as $f_{l_3^1}$, satisfy $p_{l_2^1} < p_{l_3^1}$, then:*

- ***L0.1.1:*** *The maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 1$ is $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} \leqslant 2\theta_L - c(2)$.*
- ***L0.1.2:*** *The maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 1$ is $max\{\theta_H - c(1), 2\theta_H - c(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \leqslant 3\theta_H - c(3)$.*
- ***L0.1.3:*** *The maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 2$ is $max\{2\theta_H - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \leqslant 3\theta_H - c(3)$.*
- ***L0.1.4:*** *The maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 3$ is $3\theta_L - c(3) < 2\theta_L - c(2)$.*

Proof. Both $f_{l_2^1}$ and $f_{l_3^1}$ are globally non-dominated, and re-denote them as $f_{ND_2^1}$ and $f_{ND_3^1}$ (so there should be $p_{ND_2^1} < p_{ND_3^1}$. According to C2.1 and C3.1, both $f_{ND_2^1}$ and $f_{ND_3^1}$ must apply.

- **Proof for L0.1.1:** Let's discuss different cases:
  - **Case L0.1.1.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_2^1}$, then f_1's expected quality is 1 according to C4.2.1. Since $p_1 \geqslant c(1)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L - c(1)$.
  - **Case L0.1.1.2:** If a seller with $q = 1$, denoted as f_1, has $p_{ND_2^1} \leqslant p_1 < p_{ND_3^1}$, then f_1's expected quality is $2 - \alpha_2 \in [1, 2]$ according to C4.2.1. Since $p_{ND_2^1} \geqslant c(2)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L(2 - \alpha_2) - c(2) = 2\theta_L - c(2) - \theta_L\alpha_2$.
  - **Case L0.1.1.3:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_3^1}$, then f_1's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$ according to C4.2.1. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L(3 - 2\alpha_1 - \beta_1) - c(3) = 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1$.
  - The inequality holds because according to (86), $c(2) - c(1) < \theta_L \Rightarrow \theta_L - c(1) < 2\theta_L - c(2)$, and according to (87), $c(3) - c(2) > \theta_L \Rightarrow 3\theta_L - c(3) < 2\theta_L - c(2)$.
- **Proof for L0.1.2:** Let's discuss different cases:
  - **Case L0.1.2.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_2^1}$, then f_1's expected quality is 1 according to C4.2.1. Since $p_1 \geqslant c(1)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H - c(1)$.
  - **Case L0.1.2.1:** If a seller with $q = 1$, denoted as f_1, has $p_{ND_2^1} \leqslant p_1 < p_{ND_3^1}$, then f_1's expected quality is $2 - \alpha_2 \in [1, 2]$ according to C4.2.1. Since $p_{ND_2^1} \geqslant c(2)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H(2 - \alpha_2) - c(2) = 2\theta_H - c(2) - \theta_H\alpha_2$.
  - **Case L0.1.2.3:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_3^1}$, then f_1's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$ according to C4.2.1. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H(3 - 2\alpha_1 - \beta_1) - c(3) = 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1$.

- The inequality holds because according to (89), $c(3) - c(2) < \theta_H \Rightarrow 2\theta_H - c(2) < 3\theta_H - c(3)$, and according to (87), $c(3) - c(2) < \theta_H \Rightarrow 2\theta_L - c(2) < 3\theta_L - c(3)$.

- **Proof for L0.1.3:** Let's discuss different cases:

  - **Case L0.1.3.1:** If an untested seller with $q = 2$, denoted as f_2, has $p_{ND_2^1} \leqslant p_2 < p_{ND_3^1}$, a $\theta = \theta_H$ buyer's expected quality is $2 - \alpha_2 \in [1, 2]$ according to C4.2.1. Since $p_{ND_2^1} \geqslant c(2)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_2 is $\theta_H(2 - \alpha_2) - c(2) = 2\theta_H - c(2) - \theta_H\alpha_2$. Then a $\theta = \theta_H$ buyer's maximum expected profit from any $q = 2$ sellers (globally non-dominated or dominated) is $max\{\theta_H \times 2 - c(2), 2\theta_H - c(2) - \theta_H\alpha_2\} = 2\theta_H - c(2)$.
  - **Case L0.1.3.2:** If an untested seller with $q = 2$, denoted as f_2, has $p_2 \geqslant p_{ND_3^1}$, then f_2's expected quality is $3 - 2\alpha_1 - \beta_1$ according to C4.2.1. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_2 is $\theta_H(3 - 2\alpha_1 - \beta_1) - c(3) = 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1$. Then a $\theta = \theta_H$ buyer's maximum expected profit from buying from any $q = 2$ sellers (globally non-dominated or dominated) is is $max\{\theta_H \times 2 - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} = max\{2\theta_H - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\}$.
  - The inequality holds because according to (89), $c(3) - c(2) < \theta_H \Rightarrow 2\theta_H - c(2) < 3\theta_H - c(3)$.

- **Proof for L0.1.4:** Let's discuss different cases:

  - Denote (one of) the globally dominated seller(s) with $q = 3$ as $f_{ND_3^1}$. According to C2.1, $f_{ND_3^1}$ must apply. According to C4.2.1, any untested seller with $q = 3$ must have an expected quality of $3 - 2\alpha_1 - \beta_1 \in [1, 3]$. On the other hand, all sellers with $q = 3$ must have $p \geqslant c(3)$. Therefore, a $\theta = \theta_L$ buyer's maximum expected profit from buying from any seller with $q = 3$ is $max\{3\theta_L - c(3), \theta_L(3 - 2\alpha_1 - \beta_1) - c(3)\} = 3\theta_L - c(3)$. The inequality holds because according to (87), $c(3) - c(2) > 4 \Rightarrow 3\theta_L - c(3) < 2\theta_L - c(2)$.

$\square$

Lemma 0.2 (L0.2). *If there exist sellers with $q = 2$ and $q = 3$ and (one of) the seller with the lowest price among $q = 2$, denoted as $f_{l_2^1}$, and (one of) the seller with the lowest price among $q = 3$, denoted as $f_{l_3^1}$, satisfy $p_{l_2^1} \geqslant p_{l_3^1}$, then:*

- ***L0.2.1:*** *The maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 1$ is $max\{\theta_H - c(1), 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2\} \leqslant 3\theta_H - c(3)$.*
- ***L0.2.2:*** *The maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 2$ is $3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2$.*

Proof. $f_{l_2^1}$ is globally dominated and $f_{l_3^1}$ is globally non-dominated, and re-denote $f_{l_3^1}$ as $f_{ND_3^1}$ (so there should be $p_{l_2^1} \geqslant p_{ND_3^1}$). According to C2.1 and C3.2, $f_{l_2^1}$ will not apply (and none of other $q = 2$ sellers, if any, will apply) and $f_{ND_3^1}$ will apply.

- **Proof for L0.2.1:** Let's discuss different cases:
  - **Case L0.2.1.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_3^1}$, then f_1's expected quality is 1 according to C4.2.3. Since $p_{ND_3^1} \geqslant c(1)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H - c(1)$.
  - **Case L0.2.1.2:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_3^1}$, then f_1's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$ according to C4.2.3. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H(3 - 2\alpha_4 - \beta_2) = 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2$.
  - The inequality holds because according to (88), $c(3) - c(1) < 2\theta_H \Rightarrow \theta_H - c(1) < 3\theta_H - c(3)$.
- **Proof for L0.2.2:** According to C4.2.3, an untested seller with $q = 2$, denoted as f_2, must have $p_2 \geqslant p_{ND_3^1}$. According to C4.2.3, f_2's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_2 is $\theta_H(3 - 2\alpha_4 - \beta_2) = 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2$.

□

Lemma 0.3 (L0.3). *If there exist sellers with $q = 2$ but not any seller with $q = 3$, denote (one of) the globally non-dominated seller(s) with $q = 2$ as $f_{ND_2^1}$, then the maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 1$ is $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_3\} \leqslant 2\theta_L - c(2)$.*

Proof. Let's discuss different cases:

- **Case L0.3.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_2^1}$. According to C4.2.2, f_1's expected quality is 1. Since $p_1 \geqslant c(1)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L - c(1)$.
- **Case L0.3.2:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_2^1}$. According to C4.2.2, f_1's expected quality is $2 - \alpha_3 \in [1, 2]$. Since $p_{ND_2^1} \geqslant c(2)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L(2 - \alpha_3) - c(2) = 2\theta_L - c(2) - \theta_L\alpha_3$.
- This inequality holds because according to (86), $c(2) - c(1) < \theta_L \Rightarrow \theta_L - c(1) < 2\theta_L - c(2)$.

□

Lemma 0.4 (L0.4). *If there exist sellers with $q = 3$ but not any seller with $q = 2$, denote (one of) the globally non-dominated seller(s) with $q = 3$ as $f_{ND_3^1}$, then*

- ***L0.4.1:*** *The maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 1$ is $max\{\theta_L - c(1), 3\theta_L - c(3) - 2\theta_L\alpha_4 - \theta_L\beta_2\} < 2\theta_L - c(2)$.*
- ***L0.4.2:*** *The maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 1$ is $max\{\theta_H - c(1), 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2\} \leqslant 3\theta_H - c(3)$.*

Proof. According to C2.1, $f_{ND_3^1}$ must apply.

- **Proof for L0.4.1:** Let's discuss different cases:
  - **Case L0.4.1.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_3^1}$. According to C4.2.3, f_1's expected quality is 1. Since $p_1 \geqslant c(1)$, a $\theta = \theta_L$ buyer's maximum expected profit from buying from f_1 is $\theta_L - c(1)$.
  - **Case L0.4.1.2:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_3^1}$. According to C4.2.3, f_1's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_L$

buyer's maximum expected profit from buying from f_1 is $\theta_L(3 - 2\alpha_1 - \beta_1) - c(3) = 3\theta_L - c(3) - 2\theta_L\alpha_4 - \theta_L\beta_2$.

  - The inequality holds because according to (86), $c(2) - c(1) < \theta_L \Rightarrow \theta_L - c(1) < 2\theta_L - c(2)$, and according to (87), $c(3) - c(2) > \theta_L \Rightarrow 3\theta_L - c(3) < 2\theta_L - c(2)$.

- **Proof for L0.4.2:** Let's discuss different cases:

  - **Case L0.4.2.1:** If a seller with $q = 1$, denoted as f_1, has $p_1 < p_{ND_3^1}$. According to C4.2.3, f_1's expected quality is 1. Since $p_1 \geqslant c(1)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H - c(1)$.

  - **Case L0.4.2.2:** If a seller with $q = 1$, denoted as f_1, has $p_1 \geqslant p_{ND_3^1}$. According to C4.2.3, f_1's expected quality is $3 - 2\alpha_1 - \beta_1 \in [1, 3]$. Since $p_{ND_3^1} \geqslant c(3)$, a $\theta = \theta_H$ buyer's maximum expected profit from buying from f_1 is $\theta_H(3 - 2\alpha_1 - \beta_1) - c(3) = 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2$.

  - The inequality holds because according to (88), $c(3) - c(1) < 2\theta_H \Rightarrow \theta_H - c(1) < 3\theta_H - c(3)$.

□

Lemma 1 (L1). *If in a strategy profile, no seller applies, then this strategy profile cannot be a PBE.*

Proof. If no seller applies, then according to C1, C2.1 and C3.1, all sellers must have $q = 1$, and every (untested) seller's expected quality is also 1 (according to C4.2.4), so only the seller with the lowest price will have a positive demand, if any seller has a positive demand (if all sellers have zero demand, then the only reason is that their prices are all too high, so obviously any seller would have the incentive to deviate by lowering her price).

- **Case 1:** If all sellers' prices are higher than $c(1)$.

  - **Case 1.1:** If not all sellers' prices are the same. Denote the seller with the highest price as f_h and the seller with the lowest price as f_l. f_h must have a 0 demand and thus a 0 expected profit, and she must have the incentive to deviate to $(1,\ p_l - \epsilon,\ Not\ Apply)$, where ϵ can be any number which satisfies $\epsilon < p_l - c(1)$, and then she would have a positive expected demand and thus a positive expected profit.

- If all sellers' prices are the same. Then every seller must have an expected demand of 1. Then any seller must have the incentive to reduce their price by ϵ, where ϵ is small enough, so that her expected demand becomes s, but her markup is only reduced by a little, so her expected profit is still increased.

- **Case 2:** If at least one seller's price is $c(1)$. Then the seller(s) with $p = c(1)$ will have an expected profit of 0. Suppose the lowest price among all the other sellers is $p = c(1) + \tau$ ($\tau \geq 0$). The seller(s) with $p = 1$ must have an incentive to deviate to $(2,\ c(2) + \epsilon,\ Apply)$, where ϵ is small enough such that all $\theta = \theta_L$ will strictly prefer this deviated seller (i.e., $2\theta_L - (c\,(2) + \epsilon) > \theta_L - (c\,(1) + \tau) \iff \epsilon < \tau + c\,(1) - c\,(2) + \theta_L$. According to (86), $c\,(2) - c\,(1) < \theta_L \Rightarrow\ c\,(1) - c\,(2) + \theta_L > 0$, so there must exist $\epsilon > 0$ that is small enough) to get a positive expected profit.

□

Lemma 2 (L2). *If in a strategy profile, there do not exist sellers with $q = 3$, then this strategy profile cannot be a PBE, when* $\begin{cases} \alpha_3 > 0 \\ \alpha_1 + \beta_1 > 0 \end{cases}$.

Proof. According to C1, C3.1 and C3.2, if there exist sellers with $q = 2$, the globally non-dominated one(s) must apply, and all other sellers (including sellers with $q = 1$, if any, and globally dominated sellers with $q = 2$, if any) will not apply. Denote (one of) the globally non-dominated seller(s) with $q = 2$ as $f_{ND_2^1}$. If there exist sellers with $q = 1$, then according to C1, no seller with $q = 1$ will apply. Denote the seller with the lowest price among $q = 1$ as f_l. We then prove the following lemmas when there does not exist any seller with $q = 3$:

- **Lemma 2.1 (L2.1):** Suppose there does not exist any seller with $q = 3$, and there exist seller(s) with $q = 2$. Any seller with $p > p_{ND_2^1}$, denoted as f_h, must have a 0 expected demand and thus a 0 expected profit.

  - Proof: This other seller must have an expected quality of $2 - \alpha_3 \in [1, 2]$ according to C4.2.2. $f_{ND_2^1}$ must be strictly preferred to f_h by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because

$2\theta_L - p_{ND^1_2} > \theta_L(2-\alpha_3) - p_h$ and $2\theta_H - p_{ND^1_2} > \theta_H(2-\alpha_3) - p_h$), so she must have a 0 expected demand.

- **Lemma 2.2 (L2.2):** Suppose there does not exist any seller with $q = 3$, and there exist seller(s) with $q = 2$. If there exist at least two sellers with $q = 1$, then if any seller with $q = 1$, denoted as f_i, has $p_i > p_l$, then f_i must have a 0 expected profit.
  - Proof:
    * **Case L2.2.1:** If $p_i < p_{ND^1_2}$, then there must be $p_l < p_{ND^1_2}$, and thus both f_l and f_i's expected qualities are 1 according to C4.2.2, but $p_i > p_l$, so f_l must be strictly preferred to f_i, so f_i must have a 0 expected demand.
    * **Case L2.2.2:** If $p_i \geqslant p_{ND^1_2}$, then f_i has an expected quality of $2 - \alpha_3$ according to C4.2.2. When $\alpha_3 > 0$, we have $2-\alpha_3 < 2$, and then $f_{ND^1_2}$ must be strictly preferred to f_i by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because $2\theta_L - p_{ND^1_2} > \theta_L(2-\alpha_3) - p_i$ and $2\theta_H - p_{ND^1_2} > \theta_H(2-\alpha_3) - p_i$), so f_i must have a 0 expected demand.
- **Lemma 2.3 (L2.3):** Suppose there does not exist any seller with $q = 3$, and there exist seller(s) with $q = 2$. If any seller with $q = 2$ has $p = c\,(2)$, then this strategy profile cannot be a PBE.
  - Proof: This seller, denoted as f_2, must have a 0 expected profit, because she has a 0 markup. Then she must have the incentive to deviate to $(3,\ c(3)+\epsilon,\ Apply)$, where ϵ is small enough, so that all $\theta = \theta_H$ buyers will strictly prefer her product (because when $\alpha_1 + \beta_1 > 0$, there must be $2\alpha_1 + \beta_1 > 0$, and then $\theta = \theta_H$ buyers' expect profit is at most $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c\,(3)$ from any $q = 1$ seller according to L0.1.2, and at most $max\{2\theta_H - c\,(2)\,, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ from any $q = 2$ seller according to L0.1.3, both of which are smaller than that from f_2, which is $3\theta_H - (c\,(3) + \epsilon) = 3\theta_H - c\,(3) - \epsilon > max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 2\theta_H - c\,(2)\,, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\}$, then she would have a positive expected profit.
- **Lemma 2.4 (L2.4):** Suppose there does not exist any seller with $q = 3$, and there exist seller(s) with $q = 2$. If any seller with $q = 1$ has $p = c(1)$, then this strategy profile cannot

be a PBE.

- Proof: This seller with $q = 1$ and $p = c(1)$, denoted as f_1, must have an expected profit of 0, regardless of whether she has any expected demand, because she has a 0 markup. Then she must have the incentive to deviate to $(3,\ c(3)+\epsilon,\ Apply)$, where ϵ is small enough, so that all $\theta = \theta_H$ buyers will strictly prefer her product (because when $\alpha_1 + \beta_1 > 0$, there must be $2\alpha_1 + \beta_1 > 0$, and then $\theta = \theta_H$ buyers' expect profit is at most $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ from any $q = 1$ seller according to L0.1.2, and at most $max\{2\theta_H - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\}$ from any $q = 2$ seller according to L0.1.3, both of which are smaller than that from f_2, which is $3\theta_H - (c\,(3) + \epsilon) = 3\theta_H - c\,(3) - \epsilon > max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 2\theta_H - c\,(2)\,, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\}$, then she would have a positive expected profit.

Then we begin to discuss different cases.

- **Case 1:** If there exist sellers with $q = 1$ and $q = 2$.
  - **Case 1.1:** If $p_{ND_2^1} > c(2)$:
    - **Case 1.1.1:** If $f_{ND_2^1}$ has a positive expected demand and f_l, the seller with the lowest price among $q = 1$ sellers, has a 0 expected demand, then f_l must have the incentive to deviate to be identical to $f_{ND_2^1}$'s action so that she would have a positive expected demand (shared with $f_{ND_2^1}$) and thus a positive expected profit.
    - **Case 1.1.2:** If $f_{ND_2^1}$ has a 0 expected demand and f_l has a positive expected demand.
      - **Case 1.1.2.1:** If $p_l = c(1)$, then according to L2.4, it cannot be a PBE.
      - **Case 1.1.2.2:** If $p_l > c(1)$, denote the seller with the lowest price among all other $q = 2$ sellers, if any, as f_2 (and there must be $p_2 \geqslant p_{ND_2^1} > c(2)$). Then $f_{ND_2^1}$ must have the incentive to deviate to $(2, c(2)+\epsilon, Apply)$, where ϵ is small enough, to guarantee a positive expected demand (because $\theta = \theta_L$ buyers' expected profit from the deviated $f_{ND_2^1}$ is $2\theta_L - (c\,(2) + \epsilon) = 2\theta_L - c(2) - \epsilon$. When $\alpha_3 > 0$, this is larger than that from a $q = 1$ seller, which is at most

$max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_3\} < 2\theta_L - c(2)$ (this inequality holds because according to (86), $c\,(2) - c\,(1) < \theta_L \Longrightarrow \theta_L - c\,(1) < 2\theta_L - c(2)$) based on L0.3, and larger than that from any other q=2 seller, which is at most $2\theta_L - p_2 < 2\theta_L - c(2)$).

* **Case 1.1.3:** If $f_{ND_2^1}$ and f_l both have positive expected demand.
  · **Case 1.1.3.1:** If $p_l = c(1)$, then according to L2.4, it cannot be a PBE.
  · **Case 1.1.3.2:** If $p_l > c(1)$:
    - **Case 1.1.3.2.1:** If there is only 1 seller with $q = 1$ and $n-1$ sellers with $q = 2$.
      - **Case 1.1.3.2.1.1:** If at least one other seller with $q = 2$, denoted as $f_{ND_2^2}, \ldots,\ f_{ND_2^k}$ $(2 \leqslant k \leqslant n-1)$, has the same price as $f_{ND_2^1}$ (i.e., these sellers are identical to $f_{ND_2^1}$), then $f_{ND_2^1}, f_{ND_2^2}, \ldots, f_{ND_2^k}$ must share demand. Any of them will have the incentive to decrease her price by ϵ and still apply, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers (because only she alone will be tested after the deviation), and her expected profit would increase, despite of a very small decrease in the markup.
      - **Case 1.1.3.2.1.2:** If $f_{ND_2^1}$ is the unique globally non-dominated seller with $q = 2$, then according to L2.1, other sellers with $q = 2$ must have an expected demand of 0 and thus an expected profit of 0, so any of these sellers must have an incentive to deviate to be identical to $f_{ND_2^1}$'s action so that she would have a positive expected demand and thus a positive expected profit.
    - **Case 1.1.3.2.2:** If there are x seller with $q = 2$ and $(n-x)$ sellers with $q = 1$. $(1 \leqslant x \leqslant n-2)$:
      - **Case 1.1.3.2.2.1:** If at least one other seller with $q = 1$, denoted as $f_{l_2}, \ldots, f_{l_k}$ $(2 \leqslant k \leqslant n-1)$, has the same price as f_l (i.e., these sellers also have the lowest price and are identical to f_l), then $f_l, f_{l_2}, \ldots, f_{l_k}$ must share demand. Notice that in this case, it is impossible that $p_l = p_{ND_2^1}$

(because that would make $f_{ND_2^1}$ strictly preferred to f_l by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers and thus make f_l have a 0 expected demand, which would contradict with the condition in Case 1.1.3). Therefore, any of $f_l, f_{l_2}, \ldots, f_{l_k}$ will have the incentive to decrease her price by ϵ and still not apply, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers, and her expected profit would increase, despite of a very small decrease in the markup.

- **Case 1.1.3.2.2.2:** If f_l is the unique seller with the lowest price among sellers with $q = 1$, then other sellers with $q = 1$, whose price is higher than f_l, must have an expected demand of 0 and thus an expected profit of 0 according to L2.2, so any of these sellers must have an incentive to deviate to be identical to f_l's action so that she would have a positive demand and thus a positive expected profit (due to a positive markup).

* **Case 1.1.4:** If $f_{ND_2^1}$ and f_l both have 0 expected demand (and thus both of them have a 0 expected profit), then according to L2.1 and L2.2, all buyers will choose not to buy from any seller (and thus all sellers have a 0 expected profit). The only possibility for this case is that for any buyer, the expected profit from buying from any seller is non-positive. Then any seller would have the incentive to deviate to, for example, $(2,\ c(2) + \epsilon, Apply)$, where $\epsilon < 2\theta_H - c(2)$, so that buyers with $\theta = \theta_H$ would buy from her and thus she would have a positive expected profit.

– **Case 1.2:** If $p_{ND_2^1} = c(2)$, then according to L2.3, we know that it cannot be a PBE.

- **Case 2:** All sellers have $q = 1$. In this case, according to C1, no seller will apply. Then according to L1, it cannot be a PBE.

- **Case 3:** All sellers have $q = 2$. In this case, according to C3.1, $f_{ND_2^1}$ must apply.

  – **Case 3.1:** If$p_{ND_2^1} = c(2)$, then according to L2.3, we know that it cannot be a PBE.

  – **Case 3.2:** If $c(2) < p_{ND_2^1} < 2\theta_H$, then $p_{ND_2^1}$ must have a positive expected demand and thus a positive expected profit.

    * **Case 3.2.1:** If at least one other seller with $q = 2$, denoted as $f_{ND_2^2}, \ldots,\ f_{ND_2^k}$ $(2 \leqslant$

$k \leqslant n-1$), has the same price as $f_{ND_2^1}$ (i.e., these sellers are identical to $f_{ND_2^1}$), then $f_{ND_2^1}, f_{ND_2^2}, \ldots, f_{ND_2^k}$ must share demand. Any of them will have the incentive to decrease her price by ϵ and still apply, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers (because only she alone will be tested after the deviation), and her expected profit would increase, despite of a very small decrease in the markup.

* **Case 3.2.2:** If $f_{ND_2^1}$ is the unique globally non-dominated seller with $q = 2$, then according to L2.1, other sellers with $q = 2$ must have an expected demand of 0 and thus an expected profit of 0, so any of these sellers must have an incentive to deviate to be identical to $f_{ND_2^1}$'s action so that she would have a positive demand and thus a positive expected profit.

– **Case 3.3:** If $p_{ND_2^1} \geqslant 2\theta_H$, then $f_{ND_2^1}$ must have a 0 expected demand and thus a 0 expected profit. According to L2.1, any other seller must have a 0 expected profit too. Then any seller must have the incentive to deviate to, for example, $(2,\ c\,(2)+\epsilon, Apply)$, where $\epsilon < 2\theta_H - c\,(2)$, so that all $\theta = \theta_H$ buyers will strictly prefer her product, and then she would have a positive expected profit.

We have discussed all cases and do not find any PBE.

□

Lemma 3 (L3). *If in a strategy profile, there do not exist sellers with $q = 2$, then this strategy profile cannot be a PBE when* $\begin{cases} \alpha_4 + \beta_2 > 0 \\ \alpha_2 > 0 \\ \alpha_1 + \beta_1 > 0 \end{cases}$.

Proof. According to C1, C2.1 and C2.2, if there exist sellers with $q = 3$, the globally non-dominated one(s) must apply, and all other sellers (including sellers with $q = 1$, if any, and globally dominated sellers with $q = 3$, if any) will not apply. Denote (one of) the globally non-dominated seller(s) with $q = 3$ as $f_{ND_3^1}$. If there exist sellers with $q = 1$, then according to C1, no seller with $q = 1$ will apply. Denote the seller with the lowest price among $q = 1$ as f_l. We then prove the following lemmas when there does not exist any seller with $q = 2$:

- **Lemma 3.1 (L3.1):** Suppose that in a strategy profile, there do not exist sellers with $q = 2$, and there exist sellers with $q = 3$. Any seller with $p > p_{ND_3^1}$, denoted as f_h, must have a 0 expected demand and thus a 0 expected profit.
  - Proof: f_h must have an expected quality of $3 - 2\alpha_4 - \beta_2$ according to C4.2.3. $f_{ND_3^1}$ must be strictly preferred to f_h by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because $3\theta_L - p_{ND_3^1} > \theta_L(3 - 2\alpha_4 - \beta_2) - p_h$ and $3\theta_H - p_{ND_3^1} > \theta_H(3 - 2\alpha_4 - \beta_2) - p_h$), so f_h must have a 0 expected demand.
- **Lemma 3.2 (L3.2):** Suppose that in a strategy profile, there do not exist sellers with $q = 2$, and there exist sellers with $q = 3$. If there exist at least two sellers with $q = 1$, then if any seller with $q = 1$, denoted as f_i, has $p_i > p_l$, then f_i must have a 0 expected profit.
  - **Case L3.2.1:** If $p_i < p_{ND_3^1}$, then there must be $p_l < p_{ND_3^1}$, and thus both f_l and f_i's expected qualities are 1 according to C4.2.3, but $p_i > p_l$, so f_l must be strictly preferred to f_i, so f_i must have a 0 expected demand.
  - **Case L3.2.2:** If $p_i \geqslant p_{ND_3^1}$, then f_i has an expected quality of $3 - 2\alpha_4 - \beta_2$ according to C4.2.3. Then when $a_4 + \beta_2 > 0$, there must be $2\alpha_4 + \beta_2 > 0$, so $f_{ND_3^1}$ must be strictly preferred to f_i by all $\theta = \theta_L$ and $\theta = theta_H$ buyers (because $3\theta_L - p_{ND_3^1} > \theta_L(3 - 2\alpha_4 - \beta_2) - p_i$ and $3\theta_H - p_{ND_3^1} > \theta_H(3 - 2\alpha_4 - \beta_2) - p_i$), so f_i must have a 0 expected demand.
- **Lemma 3.3 (L3.3):** Suppose that in a strategy profile, there do not exist sellers with $q = 2$, and there exist sellers with $q = 3$. If any seller with $q = 3$ has $p = c(3)$, then this strategy profile cannot be a PBE.
  - Proof: This seller, denoted as f_3, must have a 0 expected profit, because she has a 0 markup. Then she must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where ϵ is small enough, so that all $\theta = \theta_L$ buyers will strictly prefer her product (because $\begin{cases} \alpha_1 + \beta_1 > 0 \\ \alpha_2 > 0 \end{cases}$, there must be $\begin{cases} 2\theta_L\alpha_1 + \theta_L\beta_1 > 0 \\ \alpha_2 > 0 \end{cases}$, and then $\theta = \theta_L$ buyers' expect profit is at most $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$ from any $q = 1$ seller according to L0.1.1, and at most

$3\theta_L - c(3) < 2\theta_L - c(2)$ from any $q = 3$ seller according to L0.1.4, both of which are smaller than that from the deviated f_3, which is $2\theta_L - (c(2) + \epsilon) = 2\theta_L - c(2) - \epsilon > max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1, 3\theta_L - c(3)\}$), and then she would have a positive expected profit.

- **Lemma 3.4 (L3.4):** Suppose that in a strategy profile, there do not exist sellers with $q = 2$, and there exist sellers with $q = 3$. If any seller with $q = 1$ has $p = c(1)$, then this strategy profile cannot be a PBE.
  - Proof: This seller, denoted as f_1, must have a 0 expected profit, because she has a 0 markup. Then she must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where ϵ is small enough, so that all $\theta = \theta_L$ buyers will strictly prefer her product (because when $\alpha_1 + \beta_1 > 0$, there must be $2\alpha_1 + \beta_1 > 0 \Rightarrow 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1 < 3\theta_L - c(3)$, and $\alpha_2 > 0$, and then $\theta = \theta_L$ buyers' expect profit is at most $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$ from any $q = 1$ seller according to L0.1.1, and at most $3\theta_L - c(3) < 2\theta_L - c(2)$ from any $q = 3$ seller according to L0.1.4, both of which are smaller than that from the deviated f_3, which is $2\theta_L - (c(2) + \epsilon) = 2\theta_L - c(2) - \epsilon > max\{3\theta_L - c(3), \theta_L - c(1), 3\theta_L - c(3) - 2\theta_L\alpha_4\}$), and then she would have a positive expected profit.

Then we discuss different cases.

- **Case 1:** If there exist sellers with $q = 1$ and $q = 3$.
  - **Case 1.1:** If $p_{ND_3^1} > c(3)$:
    - **Case 1.1.1:** If $f_{ND_3^1}$ has a positive expected demand and f_l, the seller with the lowest price among $q = 1$ sellers, has a 0 expected demand, then f_l must have the incentive to deviate to be identical to $f_{ND_3^1}$'s action so that she would have a positive expected demand (shared with $f_{ND_3^1}$) and thus a positive expected profit.
    - **Case 1.1.2:** If $f_{ND_3^1}$ has a 0 expected demand and f_l has a positive expected demand.
      - **Case 1.1.2.1:** If $p_l = c(1)$, then according to L3.4, it cannot be a PBE.

- **Case 1.1.2.2:** If $p_l > c(1)$, denote the seller with the lowest price among all other $q = 3$ sellers, if any, as f_3 (and there must be $p_3 \geqslant p_{ND'_3} > c\,(3)$). Then $f_{ND_3^1}$ must have the incentive to deviate to $(3, c(3)+\epsilon, Apply)$, where ϵ is small enough, to guarantee a positive expected demand (because $\theta = \theta_H$ buyers' expected profit from the deviated $f_{ND_3^1}$ is $3\theta_H - (c\,(3) + \epsilon) = 3\theta_H - c(3) - \epsilon$. When $\alpha_4 + \beta_2 > 0$, there is $2\theta_H\alpha_4 + \theta_H\beta_2 > 0$, so this is larger than that from any $q = 1$ seller, which is at most $max\{\theta_H - c\,(1)\,,\; 3\theta_H - c\,(3) - 2\theta_H\alpha_4 - 2\theta_H\beta_2\} < 3\theta_H - c(3)$ based on L0.4.2, and larger than that from any other $q = 3$ seller, which is at most $3\theta_H - p_3 < 3\theta_H - c(3)$).

* **Case 1.1.3:** If $f_{ND_3^1}$ and f_l both have positive expected demand. In this case, using the same reasoning as that in Lemma 2 Case 1.1.3, it can be proved that the strategy profile cannot be a PBE.

* **Case 1.1.4:** If $f_{ND_3^1}$ and f_l both have 0 expected demand (and thus both of them have a 0 expected profit), then according to L3.1 and L3.2, all buyers will choose not to buy from any seller (and thus all sellers have a 0 expected profit). The only possibility for this case is that for any buyer, the expected profit from buying from any seller is non-positive. Then any seller would have the incentive to deviate to, for example, $(2,\; c(2) + \epsilon, Apply)$, where $\epsilon < 2\theta_H - c\,(2)$, so that buyers with $\theta = \theta_H$ would buy from her and thus she would have a positive expected profit.

– **Case 1.2:** If $p_{ND_3^1} = c(3)$, then according to L3.3, we know that it cannot be a PBE.

- **Case 2:** All sellers have $q = 1$. In this case, according to C1, no seller will apply. Then according to L1, it cannot be a PBE.

- **Case 3:** All sellers have $q = 3$. In this case, according to C2.1, $f_{ND_3^1}$ must apply and any seller with a price higher than $p_{ND_3^1}$ must have an expected quality of $3 - 2\alpha_4 - \beta_2$ according to C4.2.3.

– **Case 3.1:** If $p_{ND_3^1} = c(3)$, then according to L3.3, we know that it cannot be a PBE.

– **Case 3.2:** If $c\,(3) < p_{ND_3^1} < 3\theta_H$, then $p_{ND_3^1}$ must have a positive expected demand and thus a positive expected profit.

* **Case 3.2.1:** If at least one other seller with $q = 3$, denoted as $f_{ND_3^2}, \ldots, f_{ND_3^k}$ $(2 \leqslant k \leqslant n-1)$, has the same price as $f_{ND_3^1}$ (i.e., these sellers are identical to $f_{ND_3^1}$), then $f_{ND_3^1}, f_{ND_3^2}, \ldots, f_{ND_3^k}$ must share demand. Any of them will have the incentive to decrease her price by ϵ and apply, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers (because only she alone will be tested after the deviation), and her expected profit would increase, despite of a very small decrease in the markup.

* **Case 3.2.2:** If $f_{ND_3^1}$ is the unique globally non-dominated seller with $q = 3$, then according to L3.1, other sellers with $q = 3$ must have an expected demand of 0 and thus an expected profit of 0, so any of these sellers must have an incentive to deviate to be identical to $f_{ND_3^1}$'s action so that she would have a positive demand and thus a positive expected profit.

- **Case 3.3:** If $p_{ND_3^1} \geqslant$, then $f_{ND_3^1}$ must have a 0 expected demand and thus a 0 expected profit. According to C3.1, any other seller must have a 0 expected profit too. Then any seller must have the incentive to deviate to, for example, $(3,\ c(3) + \epsilon, Apply)$, where $\epsilon < 3\theta_H - c(3)$, so that all $\theta = \theta_H$ buyers will strictly prefer her product, and then she would have a positive expected profit.

We have discussed all cases and do not find any PBE.

□

Lemma 4 (L4). *If in a strategy profile, there exist sellers with $q = 2$ and $q = 3$, and (one of) the seller(s) with the lowest price among $q = 2$ sellers, denoted as $f_{l_2^1}$, has $p_{l_2^1} > c(2)$, then this strategy profile cannot be a PBE when*

$$\begin{cases} \alpha_4 + \beta_2 > 0 \\ \alpha_2 > 0 \\ \alpha_1 + \beta_1 > 0 \end{cases}.$$

Proof. We first prove the following lemma when there exist sellers with $q = 2$ and $q = 3$:

- **Lemma 4.1 (L4.1):** Suppose there exist sellers with $q = 2$ and $q = 3$. Any seller with $p > p_{l_2^1}$, denoted as f_h, must have a 0 expected demand and thus a 0 expected profit.

- Proof: Denote (one of) the globally non-dominated seller(s) with $q = 3$ as $f_{ND^1_3}$.
  - **Case L4.1.1:** If $p_{l^1_2} < p_{ND^1_3}$, then $f_{l^1_2}$ is globally non-dominated and thus must apply according to C3.1, then:
    - **Case L4.1.1.1:** If $p_{l^1_2} < p_h < p_{ND^1_3}$, then f_h must have an expected quality of $2-\alpha_2$ according to C4.2.1, so $f_{l^1_2}$ must be strictly preferred to f_h by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because when $a_2 > 0$, $2\theta_L - p_{l^1_2} > \theta_L(2-\alpha_2) - p_h$ and $2\theta_H - p_{l^1_2} > \theta_H(2-\alpha_2) - p_h$), so f_h must have a 0 expected demand.
    - **Case L4.1.1.2:** If $p_h \geqslant p_{ND^1_3}$, then f_h must have an expected quality of $3 - 2\alpha_1 - \beta_1$ according to C4.2.1, so $f_{l^1_2}$ must be strictly preferred to $f_{ND^1_3}$ by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because when $\alpha_1 + \beta_1 > 0$, there must be $2\alpha_1 + \beta_1 > 0$, and then there is $3 - 2\alpha_1 - \beta_1 < 3$, and thus $3\theta_L - p_{ND^1_3} > \theta_L(3-2\alpha_1-\beta_1) - p_h$ and $3\theta_H - p_{ND^1_3} > \theta_H(3-2\alpha_1-\beta_1) - p_h$), so f_h must have a 0 expected demand.
  - **Case L4.1.2:** If $p_{l^1_2} \geqslant p_{ND^1_3}$, then $f_{l^1_2}$ is globally dominated and thus will not apply according to C3.2 (and none of other sellers with $q = 2$ will apply), then both $f_{l^1_2}$ and f_h must have an expected quality of $3 - 2\alpha_4 - \beta_2$ according to C4.2.3. When $\alpha_4 + \beta_2 > 0$, there must be $2\alpha_4 + \beta_2 > 0$, so there is $3 - 2\alpha_4 - \beta_2 < 3$, and thus $f_{ND^1_3}$ must be strictly preferred to f_h by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because $3\theta_L - p_{l^1_2} > \theta_L(3 - 2\alpha_4 - \beta_2) - p_h$ and $3\theta_H - p_{l^1_2} > \theta_H(3 - 2\alpha_4 - \beta_2) - p_h$), so f_h must have a 0 expected demand.

Now let's discuss the following cases:

- **Case 1:** If $f_{l^1_2}$ has a positive demand, then she must have a positive expected profit (due to a positive markup). In this case, there must be $p_{l^1_2} < p_{ND^1_3}$ and $f_{l^1_2}$ is globally non-dominated and must apply according to C3.1, because otherwise she would have a 0 expected demand (if $p_{l^1_2} \geqslant p_{ND^1_3}$, then $f_{l^1_2}$ will not apply according to C3.2 and would have an expected quality of $3 - 2\alpha_4$ according to C4.2.3. When $\alpha_4 + \beta_2 > 0$, $3 - 2\alpha_4 - \beta_2 < 3$, and then $f_{ND^1_3}$ would be strictly preferred to $f_{l^1_2}$ by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers, because $3\theta_L - p_{ND^1_3} > \theta_L(3 - 2\alpha_4 - \beta_2) - p_{l^1_2}$ and $3\theta_H - p_{ND^1_3} > \theta_H(3 - 2\alpha_4 - \beta_2) - p_{l^1_2}$).

- **Case 1.1:** If at least one other seller with $q = 2$, denoted as $f_{l_2^2}, \ldots, f_{l_2^k}$ $(2 \leqslant k \leqslant n-1)$, has the same price as $f_{l_2^1}$ (i.e., these sellers are identical to $f_{ND_2^1}$), then $f_{l_2^1}, f_{l_2^2}, \ldots, f_{l_2^k}$ must all apply (according to C3.1) and thus share demand. Any of them will have the incentive to decrease her price by ϵ and still apply, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers (because only she alone will be tested after the deviation), and her expected profit would increase, despite of a very small decrease in the markup.
- **Case 1.2:** If $f_{l_2^1}$ is the unique seller with the lowest price among sellers with $q = 2$, then according to L4.1, other sellers with $q = 2$ must have an expected demand of 0 and thus an expected profit of 0, so any of these sellers must have an incentive to deviate to be identical to $f_{l_2^1}$'s action so that she would have a positive demand and thus a positive expected profit.

- **Case 2:** If $f_{l_2^1}$ has a 0 expected demand, then she must have a 0 expected profit, then according to L4.1, other sellers with $q = 2$ must have an expected demand of 0 and thus an expected profit of 0 (denote the seller with the lowest price among all other $q = 2$ sellers, if any, as f_2, and there must be $p_2 \geqslant p_{l_2^1} > c(2)$). The only possibility for this case is that $p_{l_2^1}$ is too high. $f_{l_2^1}$ must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where ϵ is small enough, to guarantee that all $\theta = \theta_L$ buyers would strictly prefer her (because when $\alpha_1 + \beta_1 > 0$, there must be $2\alpha_1 + \beta_1 > 0 \Rightarrow -2\theta_L\alpha_1 - \theta_L\beta_1 < 0$, and then there is $2\theta_L - c\,(2) - 2\theta_L\alpha_1 - \theta_L\beta_1 < 2\theta_L - c(2)$, and since $\alpha_2 > 0$, there is $2\theta_L - c\,(2) - \alpha_2 < 2\theta_L - c(2)$. Thus, the maximum expected profit a $\theta = \theta_L$ buyer can get from a $q = 1$, according to L0.1.1, is $max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$, and the maximum expected profit a $\theta = \theta_L$ buyer can get from a $q = 3$, according to L0.1.4, is $3\theta_L - c\,(3) < 2\theta_L - c(2)$. The maximum expected profit a $\theta = \theta_L$ buyer can get from any other seller with $q = 2$ who must have a price no less than the deviated $p_{l_2^1}$ is $2\theta_L - p_2 < 2\theta_L - c(2)$. Then a $\theta = \theta_L$ buyer's expected profit from the deviated $f_{l_2^1}$ would be $2\theta_L - (c\,(2) + \epsilon) = 2\theta_L - c(2) - \epsilon > max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1, 3\theta_L - c\,(3)\,, 2\theta_L - p_2\}$).
- We have discussed all cases and do not find any PBE.

□

Lemma 5 (L5). *If in a strategy profile, there exist sellers with $q = 2$ and $q = 3$, and the globally non-dominated seller(s) with $q = 3$, denoted as $f_{ND_3^1}$, has $p_{ND_3^1} > c(3)$, then this strategy profile cannot be a PBE when* $\begin{cases} \alpha_4 + \beta_2 > 0 \\ \alpha_1 + \beta_1 > 0 \end{cases}$.

Proof. We first prove the following lemma when there exist sellers with $q = 2$ and $q = 3$:

- **Lemma 5.1 (L5.1):** Any seller with $p > p_{ND_3^1}$, denoted as f_h, must have a 0 expected demand and thus a 0 expected profit.
  - Proof: Denote (one of) the globally non-dominated seller(s) with $q = 3$ as $f_{ND_3^1}$. According to C2.1, $f_{ND_3^1}$ must apply. According to C4.2.1 and C4.2.3, any untested seller with $p_h > p_{ND_3^1}$ must have an expected quality of $3 - 2\alpha_1 - \beta_1$ or $3 - 2\alpha_4 - \beta_2$. $f_{ND_3^1}$ must be strictly preferred to f_h by all $\theta = \theta_L$ and $\theta = \theta_H$ buyers (because $3\theta_L - p_{ND_3^1} > \theta_L(3 - 2\alpha_1 - \beta_1) - p_h$ and $3\theta_H - p_{ND_3^1} > \theta_H(3 - 2\alpha_1 - \beta_1) - p_h$ and $3\theta_L - p_{ND_3^1} > \theta_L(3 - 2\alpha_4 - \beta_2) - p_h$ and $3\theta_H - p_{ND_3^1} > \theta_H(3 - 2\alpha_4 - \beta_2) - p_h$), so f_h must have a 0 expected demand.

Now let's discuss the following cases:

- **Case 1:** If $f_{ND_3^1}$ has a positive expected demand, then she must have a positive expected profit (due to a positive markup).
  - **Case 1.1:** If at least one other seller with $q = 3$, denoted as $f_{ND_3^2}, \ldots, f_{ND_3^k}$ $(2 \leqslant k \leqslant n - 1)$, has the same price as $f_{ND_3^1}$ (i.e., these sellers are identical to $f_{ND_3^1}$), then $f_{ND_3^1}, f_{ND_3^2}, \ldots, f_{ND_3^k}$ must all apply share demand. Any of them will have the incentive to decrease her price by ϵ, where $\epsilon > 0$ is small enough, so that she would not need to share demand with other identical sellers (because only she alone will be tested after the deviation), and her expected profit would increase, despite of a very small decrease in the markup.
  - **Case 1.2:** If $f_{ND_3^1}$ is the unique globally non-dominated seller with $q = 3$, then according to L5.1, other sellers with $q = 3$ must have an expected demand of 0 and thus

an expected profit of 0, so any of these sellers must have an incentive to deviate to be identical to $f_{ND_3^1}$'s action so that she would have a positive demand and thus a positive expected profit.

- **Case 2:** If $f_{ND_3^1}$ has a 0 expected demand, then she must have a 0 expected profit, then according to L5.1, other sellers with $q = 3$ must have an expected demand of 0 and thus an expected profit of 0. The only possibility for this case is that $p_{ND_3^1}$ is too high. $f_{ND_3^1}$ must have the incentive to deviate to $(3, c(3)+\epsilon, Apply)$, where ϵ is small enough, to guarantee that all $\theta = \theta_H$ buyers would strictly or weakly prefer her (because when $\begin{cases} \alpha_4 + \beta_2 > 0 \\ \alpha_1 + \beta_1 > 0 \end{cases}$ there must be $\begin{cases} 2\theta_H\alpha_4 + \theta_H\beta_2 > 0 \\ 2\theta_H\alpha_1 + \theta_H\beta_1 > 0 \end{cases}$, and then according to L0.1.2 and L0.2.2, the maximum expected profit a $\theta = \theta_H$ buyer can get from a $q = 1$ seller is $max\{\theta_H - c\,(1)\,,\ 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$, and according to L0.1.3 and L0.2.3, the maximum expected profit a $\theta = \theta_H$ buyer can get from a $q = 2$ seller is $max\{2\theta_H - c\,(2)\,, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ or $3\theta_H - c\,(3) - 2\theta_H\alpha_4 - \theta_H\beta_2 < 3\theta_H - c(3)$. Then a $\theta = \theta_H$ buyer's expected profit from the deviated $f_{ND_3^1}$ would be $3\theta_H - (c\,(3) + \epsilon) = 3\theta_H - c(3) - \epsilon > max\{2\theta_H - c(1), 2\theta_H - c(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1, 3\theta_H - c(3) - 2\theta_H\alpha_4 - \theta_H\beta_2, 2\theta_H - c(2)\}$).

- We have discussed all cases and do not find any PBE.

□

Lemma 6 (L6). *Suppose* $\begin{cases} \alpha_1 + \beta_1 > 0 \\ \alpha_2 > 0 \\ \alpha_3 > 0 \\ \alpha_4 + \beta_2 > 0 \end{cases}$. *If in a strategy profile, there is only one globally non-dominated seller with $q = 2$ who has $p = c(2)$ (denoted as f_{ND_2}) and only one globally non-dominated seller with $q = 3$ who has $p = c(3)$ (denoted as f_{ND_3}) (i.e., all other sellers with $q = 2$, if any, have $p > c(2)$ and all other sellers with $q = 3$, if any, have $p > c(3)$), then this strategy profile cannot be a PBE.*

Proof. Let's discuss different cases.

- **Case 1:** If there exist globally dominated sellers with $q = 2$. Denote the globally dominated seller with $q = 2$ who has the second lowest price among all $q = 2$ sellers as $f_{D_2^l}$. $f_{D_2^l}$ will not apply according to C3.2. We know that f_{ND_2} must have a 0 expected profit due to her 0 markup.

  - **Case 1.1:** If $p_{ND_2} < p_{D_2^l} < p_{ND_3}$, then according to C4.2.1 $f_{D_2^l}$'s expected quality is $2 - \alpha_2$. Then f_{ND_2} must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where

$$\begin{cases} 2\theta_L - (c(2) + \epsilon) > \theta_L(2 - \alpha_2) - p_{D_2^l} \\ c(2) + \epsilon < p_{D_2^l} \\ 2\theta_L - (c(2) + \epsilon) > max\{\theta_L - c(1), 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} \\ 2\theta_L - (c(2) + \epsilon) > 3\theta_L - c(3) \end{cases}$$

$$\Leftrightarrow \begin{cases} \epsilon < p_{D_2^l} + \theta_L\alpha_2 - c(2) \\ \epsilon < p_{D_2^l} - c(2) \\ \epsilon < 2\theta_L - c(2) - max\{\theta_L - c(1), 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} \\ \epsilon < c(3) - c(2) - \theta_L \end{cases}$$

  (The second inequality means that the deviated f_{ND_2}'s price should still be lower than $p_{D_2^l}$ so that the deviated f_{ND_2} is still globally non-dominated. The third inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the maximum expected profit from a $q = 1$ seller, which is $max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c\,(2)$ according to L0.1.1. The fourth inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the maximum expected profit from a $q = 3$ seller, which is $3\theta_L - c\,(3) < 2\theta_L - c(2)$ according to L0.1.4), so that all $\theta = 4$ buyers will strictly prefer the deviated f_{ND_2}.

  - **Case 1.2:** If $p_{D_2^l} \geqslant p_{ND_3}$, then according to C4.2.1, $f_{D_2^l}$'s expected quality is $3 - 2\alpha_1 - \beta_1$. Then f_{ND_2} must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where

$$\begin{cases} 2\theta_L - (c(2) + \epsilon) > \theta_L(3 - 2\alpha_1 - \beta_1) - p_{D_2^l} \\ c(2) + \epsilon < p_{ND_3} = c(3) \\ 2\theta_L - (c(2) + \epsilon) > max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} \\ 2\theta_L - (c(2) + \epsilon) > 3\theta_L - c(3) \end{cases}$$

$$\Leftrightarrow \quad \begin{cases} \epsilon < p_{D_2^l} - c(2) + 2\theta_L - \theta_L(3 - 2\alpha_1 - \beta_1) \\ \epsilon < c(3) - c(2) \\ \epsilon < 2\theta_L - c(2) - max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L - \theta_L\beta_1\} \\ \epsilon < c(3) - c(2) - \theta_L \end{cases}$$

(The second inequality means that the deviated f_{ND_2}'s price should still be lower than p_{ND_3} so that the deviated f_{ND_2} is still globally non-dominated. The third inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the maximum expected profit from a $q = 1$ seller, which is $max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$ according to L0.1.1. The fourth inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the maximum expected profit from a $q = 3$ seller, which is $3\theta_L - c\,(3) < 2\theta_L - c(2)$ according to L0.1.4), so that all $\theta = \theta_L$ buyers will strictly prefer the deviated f_{ND_2}.

- **Case 2:** If there exist globally dominated sellers with $q = 3$. Denote the globally dominated seller with $q = 3$ who has the second lowest price among all $q = 3$ sellers as $f_{D_3^l}$. $f_{D_3^l}$ will not apply according to C2.2 and has an expected quality of $3 - 2\alpha_1 - \beta_1$ according to C4.2.1. We know that f_{ND_3} must have a 0 expected profit due to her 0 markup. Then f_{ND_3} must have the incentive to deviate to $(3, c(3) + \epsilon, Apply)$, where

$$\begin{cases} 3\theta_H - (c(3) + \epsilon) > \theta_H(3 - 2\alpha_1 - \beta_1) - p_{D_3^l} \\ c(3) + \epsilon < p_{D_3^l} \\ 3\theta_H - (c(3) + \epsilon) > max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \\ 3\theta_H - (c(3) + \epsilon) > max\{2\theta_H - c\,(2)\,, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \end{cases}$$

$$\Leftrightarrow \begin{cases} \epsilon > p_{D_3^l} - c(3) + 2\theta_H\alpha_1 + \theta_H\beta_1 \\ \epsilon < p_{D_3^l} - c(3) \\ \epsilon < 3\theta_H - c(3) - max\{\theta_H - c(1), 2\theta_H - c(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \\ \epsilon < 3\theta_H - c(3) - max\{2\theta_H - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \end{cases}$$

(The second inequality means that the deviated f_{ND_3}'s price should still be lower than $p_{D_3^l}$ so that the deviated f_{ND_3} is still globally non-dominated. The third inequality means that a $\theta = \theta_H$ buyer's expected profit from the deviated f_{ND_3} should be higher than the maximum expected profit from a $q = 1$ seller, which is \$$max\{\theta_H - c(1), 2\theta_H - c(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ according to L0.1.2. The fourth inequality means that a $\theta = \theta_H$ buyer's expected profit from the deviated f_{ND_3} should be higher than the maximum expected profit from a $q = 2$ seller, which is $max\{2\theta_H - c(2), 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ according to L0.1.3), so that all $\theta = \theta_H$ buyers will strictly prefer the deviated f_{ND_3}.

- **Case 3:** If there does not exist any globally dominated sellers with $q = 2$ or $q = 3$ (so that all the other $n - 2$ sellers have $q = 1$). We know that:

  - **Case 3.1:** f_{ND_2} must have a 0 expected profit due to her 0 markup. Then f_{ND_2} must have the incentive to deviate to $(2, c(2) + \epsilon, Apply)$, where
  $$\begin{cases} c(2) + \epsilon < p_{ND_3} = c(3) \\ 2\theta_L - (c(2) + \epsilon) > max\{\theta_L - c(1), 2\theta_L - c(2) - 4\alpha_2, 3\theta_L - c(3) - 2\theta_L - \theta_L\beta_1\} \\ 2\theta_L - (c(2) + \epsilon) > 2\theta_L - c(3) \end{cases}$$
  $$\Leftrightarrow \begin{cases} \epsilon < c(3) - c(2) \\ \epsilon < 2\theta_L - c(2) - max\{\theta_L - c(1), 2\theta_L - c(2) - 4\alpha_2, 3\theta_L - c(3) - 2\theta_L - \theta_L\beta_1\} \\ \epsilon < c(3) - c(2) \end{cases}$$
  (The first inequality means that the deviated f_{ND_2}'s price should still be lower than p_{ND_3} so that the deviated f_{ND_2} is still globally non-dominated. The second inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the maximum expected profit from a $q = 1$ seller, which is $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$. according to L0.1.1. The third

inequality means that a $\theta = \theta_L$ buyer's expected profit from the deviated f_{ND_2} should be higher than the expected profit from f_{ND_3}, which is $2\theta_L - c\,(3) = 2\theta_L - c(3)$), so that all $\theta = \theta_L$ buyers will strictly prefer the deviated f_{ND_2}.

– **Case 3.2:** f_{ND_3} must have the incentive to deviate to $(3, c(3) + \epsilon, Apply)$, where

$$\begin{cases} 3\theta_H - (c(3) + \epsilon) > max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \\ 3\theta_H - (c(3) + \epsilon) > 2\theta_H - c(2) \end{cases}$$

$$\Leftrightarrow \begin{cases} \epsilon < 3\theta_H - c(3) - max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} \\ \epsilon < \theta_H - c(3) + c(2) \end{cases}$$

(The first inequality means that a $\theta = \theta_H$ buyer's expected profit from the deviated f_{ND_3} should be higher than the maximum expected profit from a $q = 1$ seller, which is $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$ according to L0.1.2. The second inequality means that a $\theta = \theta_H$ buyer's expected profit from the deviated f_{ND_3} should be higher than the expected profit from f_{ND_2}, which is $2\theta_H - c\,(2)$), so that all $\theta = \theta_H$ buyers will strictly prefer the deviated f_{ND_3}.

We have discussed all cases and do not find any PBE.

□

Lemma 7 (L7). *Suppose* $\begin{cases} \alpha_1 + \beta_1 > 0 \\ \alpha_2 > 0 \\ \alpha_3 > 0 \\ \alpha_4 + \beta_2 > 0 \end{cases}$. *If in a strategy profile, there are at least two globally non-dominated sellers with* $q = 2$ *who have* $p = c(2)$*, both of which apply, and at least two globally non-dominated sellers with* $q = 3$ *who have* $p = c(3)$*, both of which apply, then no seller or buyer has an incentive to deviate.*

Proof. In this strategy profile, the testing organization will randomly select one globally non-dominated seller with $q = 2$ and $p = c(2)$, denoted as $f_{ND_2^{K\prime}}$, and one globally non-dominated seller with $q = 3$ and $p = c(3)$, denoted as $f_{ND_3^{K\prime}}$. We now prove the following lemmas in this type of strategy profiles:

- **Lemma 7.1 (L7.1):** All buyers with $\theta = \theta_L$ must buy and only buy $f_{ND_2^{K'}}$.

  – Proof: This is because $f_{ND_2^{K'}}$ maximizes a $\theta = \theta_L$ buyer's expected profit (The expected profit from $f_{ND_2^{K'}}$ is $2\theta_L - c\,(2)$. Any other seller with $q = 2$, whose price must be no lower than $p_{ND_2^{K'}}$, will either have an expected quality of $2 - \alpha_2$ (when $p_{ND_2^{K'}} \leqslant p < p_{ND_3^{K'}}$) or $3 - 2\alpha_1 - \beta_1$ (when $p \geqslant p_{ND_3^{K'}}$) according to C4.1, and thus the maximum expected profit from this other seller with $q = 2$ is $max\{\theta_L(2 - \alpha_2) - c(2), \theta_L(3 - 2\alpha_1 - \beta_1) - c(3)\} < 2\theta_L - c(2)$ (this inequality holds because according to (87), $c\,(3) - c\,(2) > \theta_L \Rightarrow 3\theta_L - c\,(3) < 2\theta_L - c(2) \Rightarrow \theta_L(3 - 2\alpha_1 - \beta_1) - c(3) < 2\theta_L - c(2)$). According to L0.1.1, the maximum expected profit from any seller with $q = 1$ is $max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$. According to L0.1.4, the maximum expected profit from any seller with $q = 3$ is $3\theta_L - c\,(3) < 2\theta_L - c(2)$).

- **Lemma 7.2 (L7.2):** All buyers with $\theta = \theta_H$ must buy and only buy $f_{ND_3^{K'}}$.

  – Proof: This is because $f_{ND_3^{K'}}$ maximizes a $\theta = \theta_H$ buyer's expected profit (The expected profit from $f_{ND_3^{K'}}$ is $3\theta_H - c\,(3) = 3\theta_H - c(3)$. Any other seller with $q = 3$, whose price must be no lower than $p_{ND_3^{K'}}$, will have an expected quality of $3 - 2\alpha_1 - \beta_1$ according to C4.1, and thus the maximum expected profit from this other seller with $q = 3$ is $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$. According to L0.1.2, the maximum expected profit from any seller with $q = 1$ is $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$. According to L0.1.3, the maximum expected profit from any seller with $q = 2$ is $max\{2\theta_H - c\,(2)\,, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$).

Now let's consider whether each seller has an incentive to deviate:

1. For the two (or more than two) globally non-dominated sellers with $q = 2$ and $p = c(2)$, their expected profits are both 0. Neither of them has an incentive to deviate unilaterally, because:

   - **Case 1:** If one of them deviates to $q = 2$ and $p > c(2)$, then according to C3.2, this deviated seller will not apply.

- **Case 1.1:** If $p < f_{ND_3^{K'}} = c(3)$, then according to C4.1, she would have an expected quality of $2 - \alpha_2$, but all $\theta = \theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(2 - \alpha_2) - p$ where $c(2) < p < c(3)$), and all $\theta = \theta_H$ buyers would still strictly prefer $f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(2 - \alpha_2) - p$ where $c(2) < p < c(3)$ so that according to (89), $c(3) - c(2) > \theta_H \Rightarrow 3\theta_H - c(3) > 2\theta_H - c(2)$). Therefore, her expected profit after deviation is still 0.
- **Case 1.2:** If $p \geqslant f_{ND_3^{K'}} = c(3)$, then according to C4.1, she would have an expected quality of $3 - 2\alpha_1 - \beta_1$, but all $\theta = \theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(3 - 2\alpha_1 - \beta_1) - p$ where $p \geqslant c(3)$ so that according to (87), $c(3) - c(2) > \theta_L \Rightarrow 2\theta_L - c(2) > 3\theta_L - c(3)$), and all $\theta = \theta_H$ buyers would still strictly prefer $f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(3 - 2\alpha_1 - \beta_1) - p$ where $p \geqslant c(3)$). Therefore, her expected profit after deviation would still be 0.

- **Case 2:** If one of them deviates to $q = 1$ and $p \geqslant c(1)$, then according to L0.1.1, the maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 1$ is $max\{\theta_L - c(1), 2\theta_L - c(2) - \theta_L\alpha_2, 3\theta_L - c(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$, which is smaller than the expected profit from $f_{ND_2^{K'}}$ (which is $2\theta_L - c(2)$), and according to L0.1.2, the maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 1$ is $max\{\theta_H - c(1), 2\theta_H - c(2) - \theta_H\alpha_2, 3\theta_H - c(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$, which is smaller than the expected profit from $f_{ND_3^{K'}}$ (which is $3\theta_H - c(3)$). Therefore, her expected demand and expected profit after deviation would still be 0.

- **Case 3:** If one of them deviates to $q = 3$ and $p \geqslant c(3)$:
  - **Case 3.1:** If her deviating price is $p = c(3)$, then she would be identical to the globally non-dominated sellers with $q = 3$ and $p = c(3)$, and thus she would still have an expected profit of 0.
  - **Case 3.2:** If her deviating price $p > c(3)$, then according to C2.2, she will not apply. Then according to C4.1, she would have an expected quality of $3 - 2\alpha_1 - \beta_1$, but all $\theta = \theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(3 - 2\alpha_1 - \beta_1) - p$ where $p > c(3)$ so that according to (87), $c(3) - c(2) > \theta_L \Rightarrow 2\theta_L - c(2) > 3\theta_L - c(3)$), and all $\theta = \theta_H$ buyers would still strictly prefer

$f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(3 - 2\alpha_1 - \beta_1) - p$ where $p > c(3)$). Therefore, her expected profit after deviation would still be 0.

- Therefore, none of the globally non-dominated sellers with $q = 2$ and $p = 4$ has the incentive to deviate.

2. For the globally non-dominated sellers with $q = 3$ and $p = c(3)$, their expected profits are both 0. Neither of them has an incentive to deviate unilaterally, because:

   - **Case 1:** If one of them deviates to $q = 3$ and $p > c(3)$, then according to C3.2, this deviated seller will not apply. Then according to C4.1, she would have an expected quality of $3 - 2\alpha_1 - \beta_1$, but all $\theta = \theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(3 - 2\alpha_1 - \beta_1) - p$ where $p > c(3)$ so that according to (87), $c\,(3) - c\,(2) > \theta_L \Rightarrow 2\theta_L - c\,(2) > 3\theta_L - c(3)$), and all $\theta = \theta_H$ buyers would still strictly prefer $f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(3 - 2\alpha_1 - \beta_1) - p$ where $p > c(3)$). Therefore, her expected profit after deviation is still 0.

   - **Case 2:** If one of them deviates to $q = 1$ and $p \geqslant c(1)$, then according to L0.1.1, the maximum expected profit a buyer with $\theta = \theta_L$ can earn from a seller with $q = 1$ is $max\{\theta_L - c\,(1)\,, 2\theta_L - c\,(2) - \theta_L\alpha_2, 3\theta_L - c\,(3) - 2\theta_L\alpha_1 - \theta_L\beta_1\} < 2\theta_L - c(2)$, which is smaller than the expected profit from $f_{ND_2^{K'}}$ (which is $2\theta_L - c\,(2)$), and according to L0.1.2, the maximum expected profit a buyer with $\theta = \theta_H$ can earn from a seller with $q = 1$ is $max\{\theta_H - c\,(1)\,, 2\theta_H - c\,(2) - \theta_H\alpha_2, 3\theta_H - c\,(3) - 2\theta_H\alpha_1 - \theta_H\beta_1\} < 3\theta_H - c(3)$, which is smaller than the expected profit from $f_{ND_3^{K'}}$ (which is $3\theta_H - c(3)$). Therefore, her expected profit after deviation would still be 0.

   - **Case 3:** If one of them deviates to $q = 2$ and $p \geqslant c(2)$:

     – **Case 3.1:** If her deviating price $p = c(2)$, then she would be identical to the two globally non-dominated sellers with $q = 2$ and $p = c(2)$, and thus she would still have an expected profit of 0.

     – **Case 3.2:** If her deviating price $p > c(2)$, then according to C2.2, she will not apply.

       * **Case 3.2.1:** If $c(2) < p < f_{ND_3^{K'}} = c(3)$, Then according to C4.1, she would

have an expected quality of $2-\alpha_2$, but all $\theta=\theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(2-\alpha_2) - p$ where $c(2) < p < c(3)$), and all $\theta=\theta_H$ buyers would still strictly prefer $f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(2-\alpha_2) - p$ where $c\,(2) < p < c(3)$). Therefore, her expected profit after deviation would still be 0.

  * **Case 3.2.2:** If $p \geqslant f_{ND_3^{K'}} = c(3)$, Then according to C4.1, she would have an expected quality of $3-2\alpha_1-\beta_1$, but all $\theta=\theta_L$ buyers would still strictly prefer $f_{ND_2^{K'}}$ (because $2\theta_L - c(2) > \theta_L(3-2\alpha_1-\beta_1) - p$ where $p \geqslant c(3)$ so that according to (87), $c\,(3) - c\,(2) > \theta_L \Rightarrow 2\theta_L - c\,(2) > 3\theta_L - c(3)$), and all $\theta=\theta_H$ buyers would still strictly prefer $f_{ND_3^{K'}}$ (because $3\theta_H - c(3) > \theta_H(3-2\alpha_1-\beta_1) - p$ where $p \geqslant c(3)$). Therefore, her expected profit after deviation would still be 0.

- Therefore, none of the globally non-dominated sellers with $q=3$ and $p=c(3)$ has the incentive to deviate.

3. For any other seller who does not have $(q=2, p=c(2))$ or $(q=3, p=c(3))$:

   - **Case 1:** If she also has $q=2$ and $p=c(2)$, or $q=3$ and $p=c(3)$, then she will also have a 0 expected profit. Using the same reasoning as the first two globally non-dominated sellers with $q=2$ and the first two globally non-dominated sellers with $q=3$, she would not have the incentive to deviate.

   - **Case 2:** If she has $q=1$, or $q=2$ and $p>c(2)$, or $q=3$ and $p>c(3)$, then according to L7.1 and L7.2, she must have an expected demand of 0 and thus an expected profit of 0. If she deviates to any bundle other than $(2, c(2), \mathit{Apply}, \mathit{Report}\ q=2)$ and $(3, c(3), \mathit{Apply}, \mathit{Report}\ q=3)$, she will still have a 0 expected demand according to L7.1 and L7.2, and thus still an expected profit of 0. If she deviates to $(2, c(2), \mathit{Apply}, \mathit{Report}\ q=2)$ or $(3, c(3), \mathit{Apply}, \mathit{Report}\ q=3)$, she will have a 0 markup and thus still have an expected profit of 0. Therefore, she would not have the incentive to deviate.

We have considered all sellers' incentives, and no seller has an incentive to deviate. □

Proposition 3. *In the SellersMayApply condition, the only pure-strategy profiles to be weak Perfect Bayesian Equilibria must have the following features:*

- γ_2 *sellers play* $(q = 2, p = c(2), Apply, Report\ q = 2)$*, with* $\gamma_2 \geqslant 2$*;*
- γ_3 *sellers play* $(q = 3, p = c(3), Apply, Report\ q = 3)$*, with* $\gamma_3 \geqslant 2$*;*
- γ_1 *sellers play* $(q = 1, p = c(2), Not\ Apply)$*, with* $\gamma_1 \geqslant 1$*;*
- $(n - \gamma_1 - \gamma_2 - \gamma_3)$ *sellers play* $(q = 1, p = c(3), Not\ Apply)$*, with* $\gamma_1 + \gamma_2 + \gamma_3 < n$*.*
- *Buyers' belief about the quality distribution of an unrevealed seller* f_t *given her price* p_t*:*
  - *If there are two revealed sellers (i.e., one with* $q = 2$*, denoted as* $f^2_{K'}$ *and the other with* $q = 3$*, denoted as* $f^3_{K'}$*), and there must be* $p^3_{K'} > p^2_{K'}$*:*

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^3_{K'}$	$\frac{\gamma_1}{\gamma_1+\gamma_2-1}$	*0*	$1 - \frac{\gamma_1}{\gamma_1+\gamma_2-1}$
if $p^2_{K'} \leqslant p_t < p^3_{K'}$	$\frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	$1 - \frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	*0*
if $p_t < p^2_{K'}$	*1*	*0*	*0*

  - *If there is only one revealed seller, and she has* $q = 2$*, denoted as* $p^2_{K'}$ $(\alpha_3 > 0)$*:*

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^2_{K'}$	α_3	$1 - \alpha_3$	*0*
if $p_t < p^2_{K'}$	*1*	*0*	*0*

  - *If there is only one revealed seller, and she has* $q = 3$*, denoted as* $p^3_{K'}$ $(\alpha_4 + \beta_2 > 0)$*:*

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^3_{K'}$	α_4	β_2	$1 - \alpha_4 - \beta_2$
if $p_t < p^3_{K'}$	*1*	*0*	*0*

  - *If there is no revealed seller, then:*

$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
1	*0*	*0*

where $\alpha_3 > 0$ *and* $\alpha_4 + \beta_2 > 0$*.*

- *Each buyer with $\theta = \theta_L$ will buy a product from the revealed seller with $q = 2$ and $p = c(2)$.*
- *Each buyer with $\theta = \theta_H$ will buy a product from the revealed seller with $q = 3$ and $p = c(3)$.*

Proof. According to L1, L2, L3, L4, L5, L6 and L7, we know that the only possible pure-strategy profiles in which no seller would have the incentive to deviate is that there are at least two sellers with $(q = 2, p = c(2), Apply, Report\ q = 2)$ and at least two sellers with $(q = 3, p = c(3), Apply, Report\ q = 3)$. In order to find Perfect Bayesian Equilibria, we need to make sure that buyers' belief about the distribution of each unrevealed seller's quality given the price is consistent with the actual quality distribution of unrevealed sellers in the equilibrium.

In L7, we require that $\alpha_1 + \beta_1 > 0$ and $\alpha_2 > 0$. This means that in the equilibrium, in addition to at least two sellers with $(q = 2, p = c(2), Apply, Report\ q = 2)$ and at least two sellers with $(q = 3, p = c(3), Apply, Report\ q = 3)$, there must exist at least one seller with $(q = 1, p = c(2), Not\ Apply)$ and at least one seller with $(q = 1, p = c(3), Not\ Apply)$, and there cannot exist any other seller with other strategy. Therefore, if there are γ_1 seller(s) with $(q = 1, p = c(2), Not\ Apply)$ and $(n - \gamma_1 - \gamma_2 - \gamma_3)$ sellers with $(q = 1, p = c(3), Not\ Apply)$, then buyers' belief about the quality distribution of an unrevealed seller f_t give her price p_t when there are two revealed sellers (i.e., one with $q = 2$ and the other with $q = 3$) must satisfy:

	$Pr(q = 1)$	$Pr(q = 2)$	$Pr(q = 3)$
if $p_t \geqslant p^3_{K'}$	$\frac{\gamma_1}{\gamma_1+\gamma_2-1}$	0	$1 - \frac{\gamma_1}{\gamma_1+\gamma_2-1}$
if $p^2_{K'} \leqslant p_t < p^3_{K'}$	$\frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	$1 - \frac{n-\gamma_1-\gamma_2-\gamma_3}{n-\gamma_1-\gamma_2-1}$	0
if $p_t < p^2_{K'}$	1	0	0

Buyers can form any arbitrary belief for all off-path situations. Therefore, the only requirements we need in the situation in which there is only one revealed seller with $q = 2$ and in the situation in which there is only one revealed seller with $q = 3$ are that $\alpha_3 > 0$ and $\alpha_4 + \beta_2 > 0$.

From L7.1 and L7.2, we know that each $\theta = \theta_L$ buyer must strictly prefer the product from the revealed seller with $(q = 2, p = c(2))$, and each $\theta = \theta_H$ buyer must strictly prefer the product from the revealed seller with $(q = 3, p = c(3))$. □

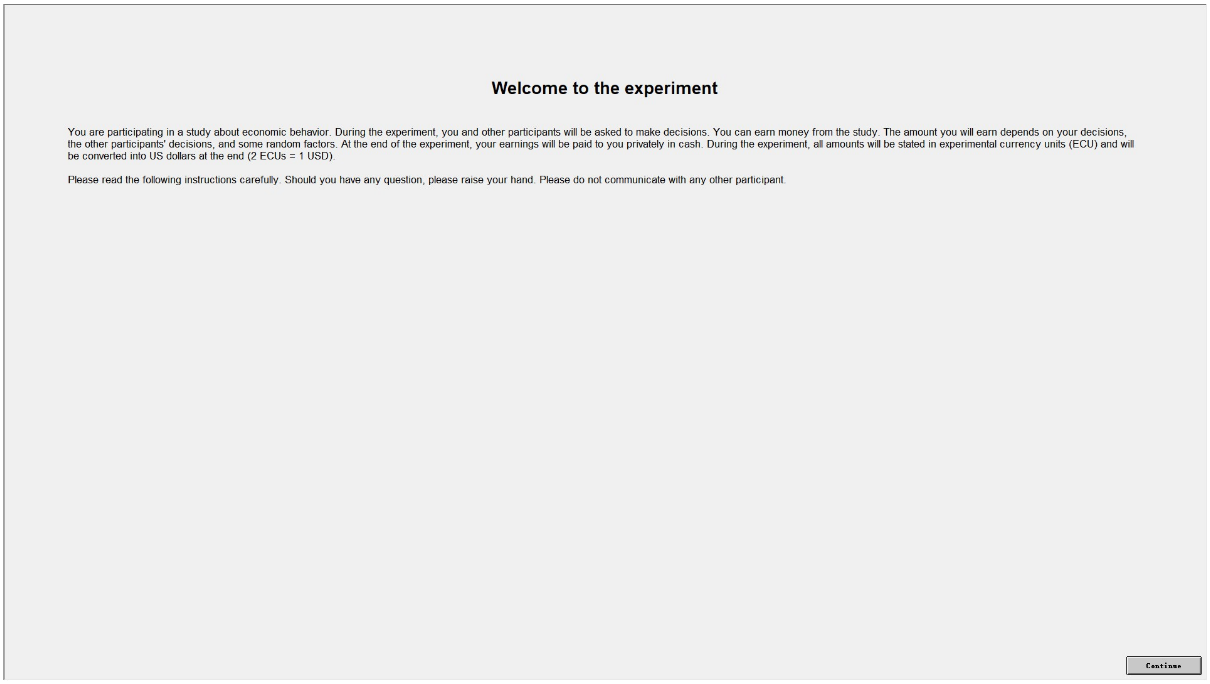
Proposition 4. *With the* RANDOMTESTING *mechanism, there does not exist any weak Perfect Bayesian Equilibrium, if any, that can yield the same buyer surplus as the* SELLERSMAYAPPLY *mechanism does.*

Proof. Suppose there existed such a strategy profile which is a weak PBE. The only possibility for a strategy profile to yield the same buyer surplus as the SELLERSMAYAPPLY mechanism does would be that all $\theta = \theta_L$ buyers strictly prefer any seller with $(q = 2, p = c(2))$ in all testing scenarios, while all $\theta = \theta_H$ buyers strictly prefer any seller with $(q = 3, p = c(3))$. On the other hand, since 2 out of n sellers are tested in each testing scenario, there does not exist any strategy profile in which there are always one seller with $(q = 2, p = c(2))$ and one seller with $(q = 3, p = c(3))$ being tested in all testing scenarios. Therefore, there must exist at least one seller with $(q = 2, p = c(2))$ or $(q = 3, p = c(3))$, denoted (one of) them as f_0, who has a positive demand in at least one testing scenario in which she is not tested. Since these sellers have a zero markup, they must all have a zero expected profit.

However, since any f_0 with $(q = 2, p = c(2))$ have a positive demand when not being tested, they must have the incentive to deviate to $(q = 1, p = c(2))$, because after deviation they would have a positive markup and would still have the same demand in all testing scenarios in which they are not tested (because only changing the price will not change the outcome buyers can see in these testing scenarios), which would result in a positive expected profit. For the same reason, any f_0 with $(q = 3, p = c(3))$ must have the incentive to deviate to $(q = 1, p = c(3))$ or $(q = 2, p = c(3))$.

□

3.B. Experimental Instructions



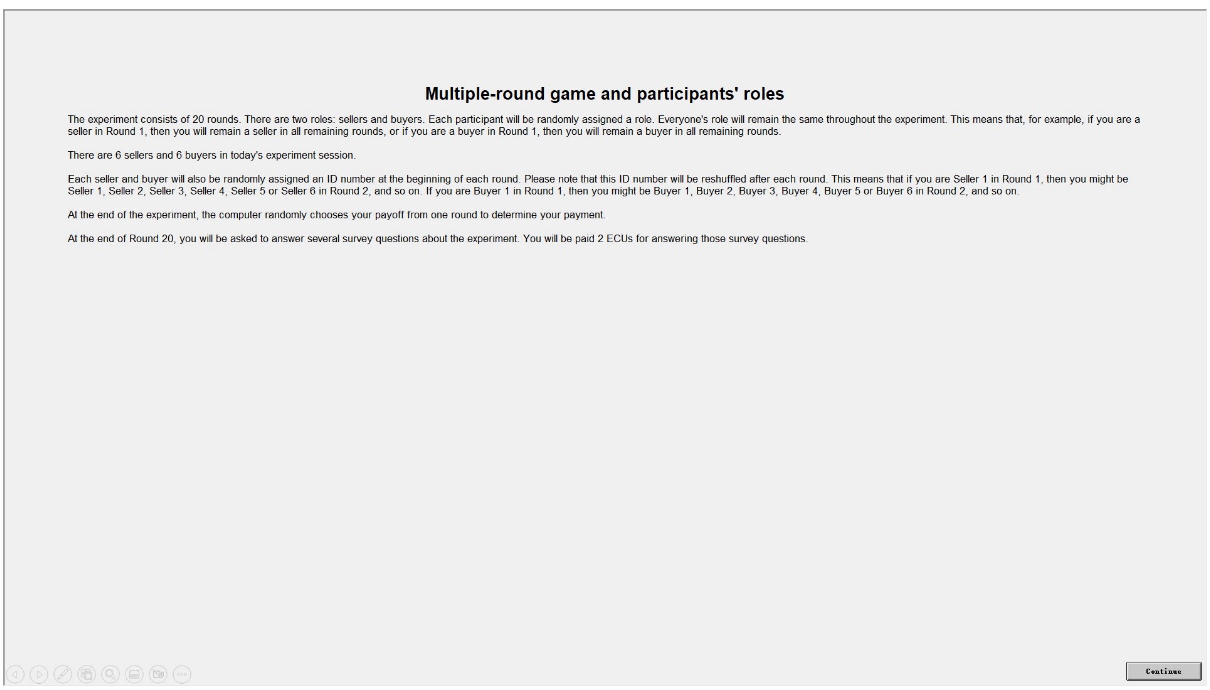
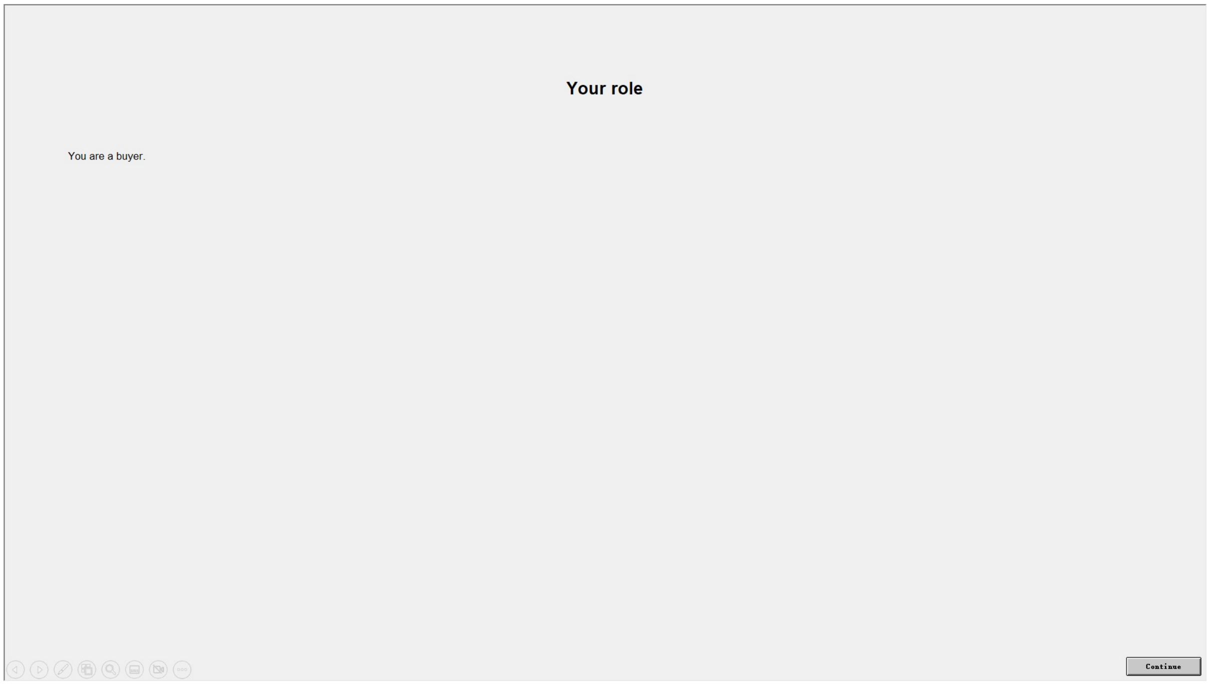


Figure 3.B.1. Experimental Instructions Screens 1-2



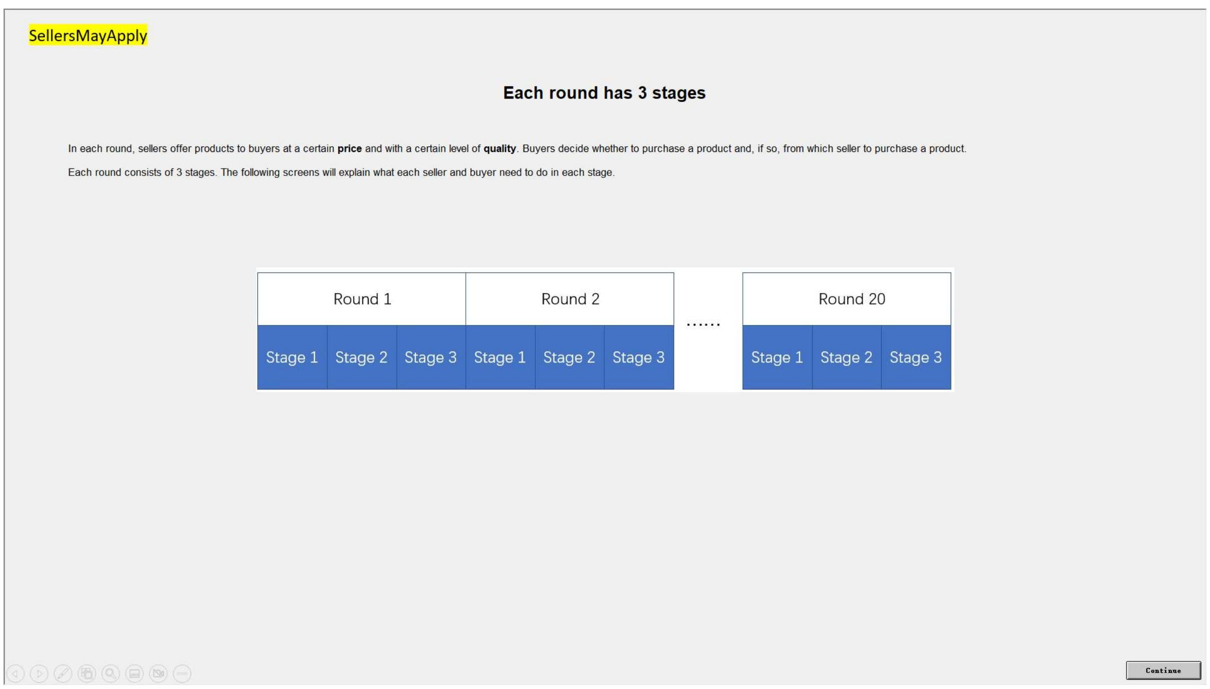
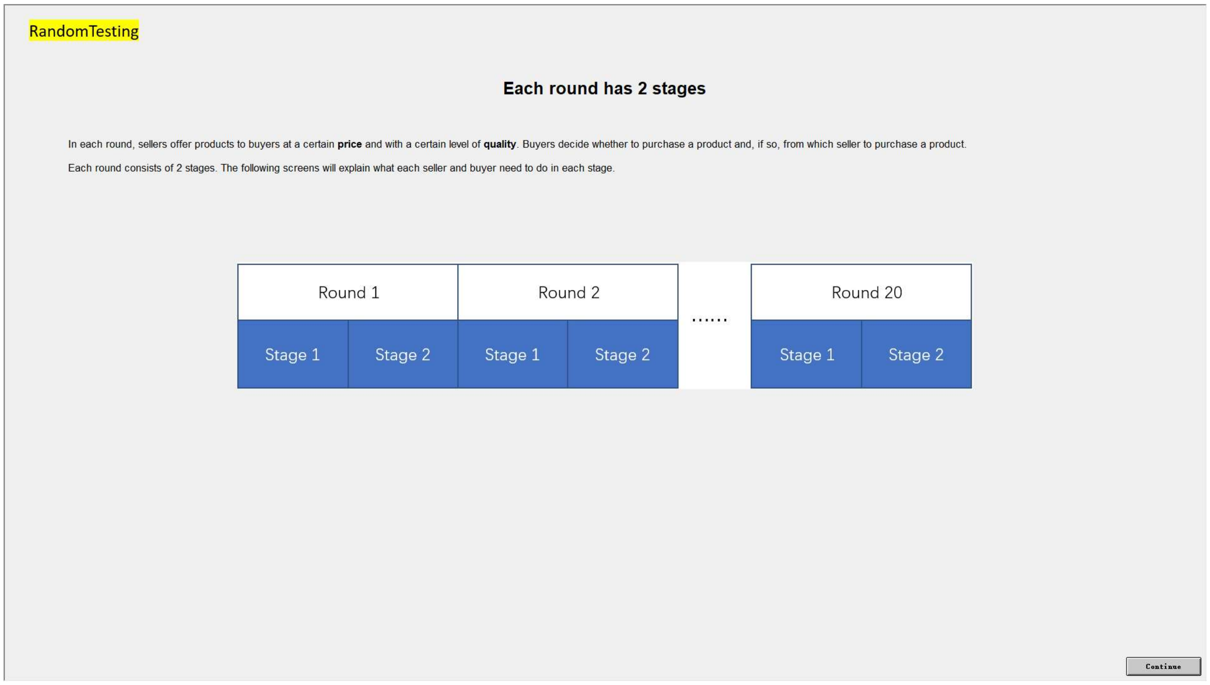


Figure 3.B.2. Experimental Instructions Screens 3-4



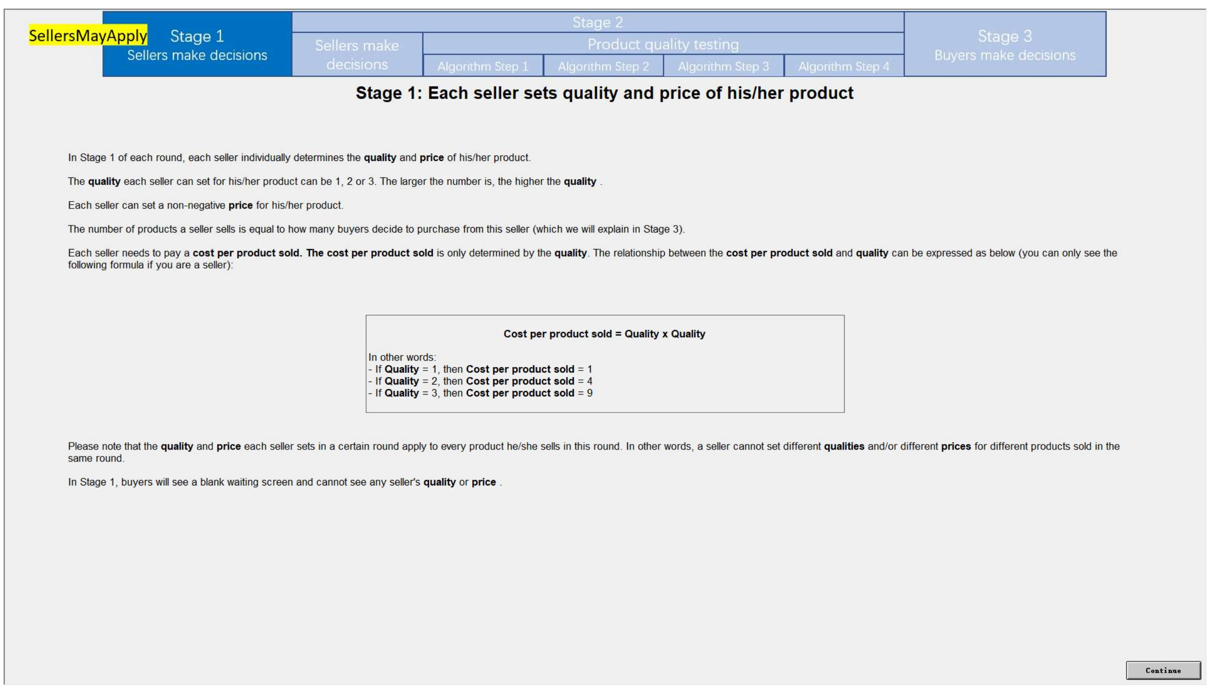
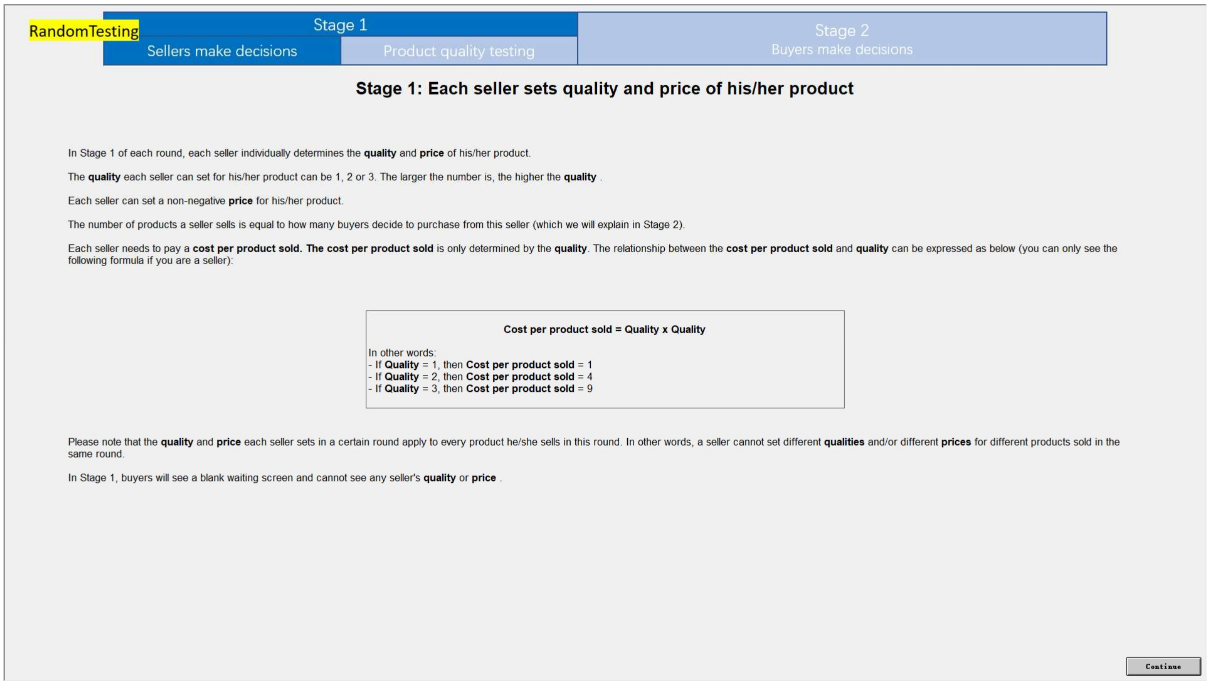


Figure 3.B.3. Experimental Instructions Screens 5-6



RandomTesting

Stage 1

Sellers make decisions

Product quality testing

Stage 2

Buyers make decisions

Stage 1: Each seller sets quality and price of his/her product

In Stage 1 of each round, each seller individually determines the **quality** and **price** of his/her product.

The **quality** each seller can set for his/her product can be 1, 2 or 3. The larger the number is, the higher the **quality** .

Each seller can set a non-negative **price** for his/her product.

The number of products a seller sells is equal to how many buyers decide to purchase from this seller (which we will explain in Stage 2).

Each seller needs to pay a **cost per product sold. The cost per product sold** is only determined by the **quality**. The relationship between the **cost per product sold** and **quality** can be expressed as below (you can only see the following formula if you are a seller):

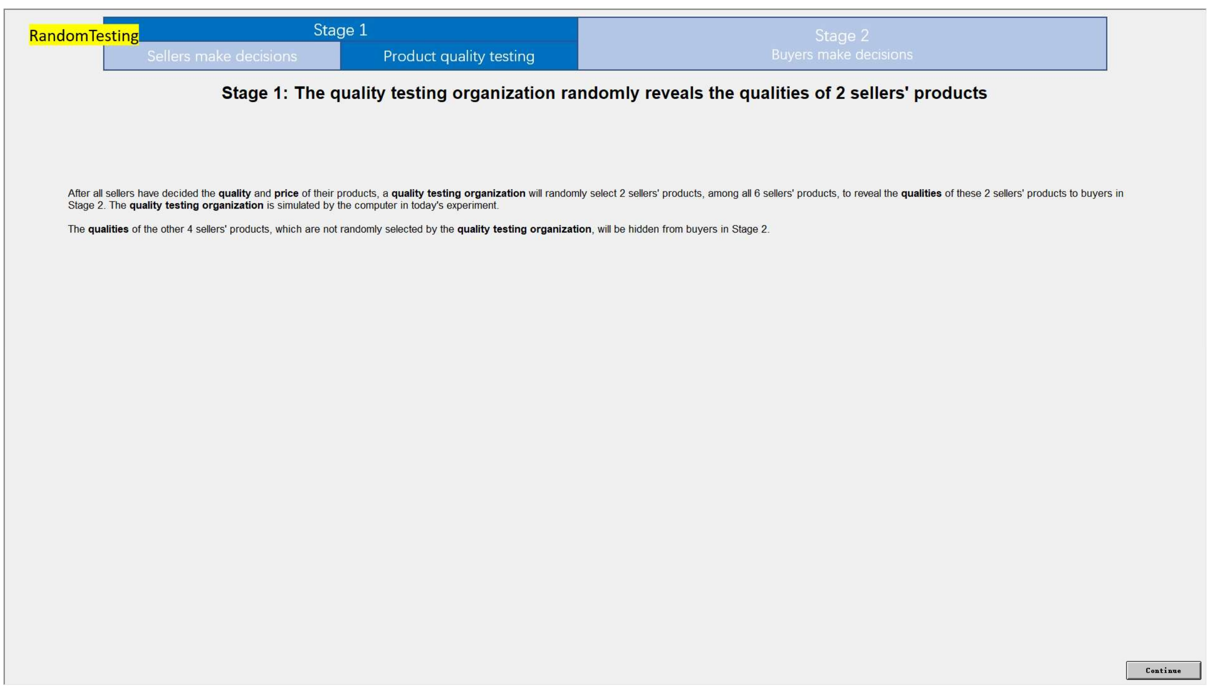
Cost per product sold = Quality x Quality

In other words:
- If **Quality** = 1, then **Cost per product sold** = 1
- If **Quality** = 2, then **Cost per product sold** = 4
- If **Quality** = 3, then **Cost per product sold** = 9

Please note that the **quality** and **price** each seller sets in a certain round apply to every product he/she sells in this round. In other words, a seller cannot set different **qualities** and/or different **prices** for different products sold in the same round.

In Stage 1, buyers will see a blank waiting screen and cannot see any seller's **quality** or **price** .

Continue



RandomTesting

Stage 1

Sellers make decisions

Product quality testing

Stage 2

Buyers make decisions

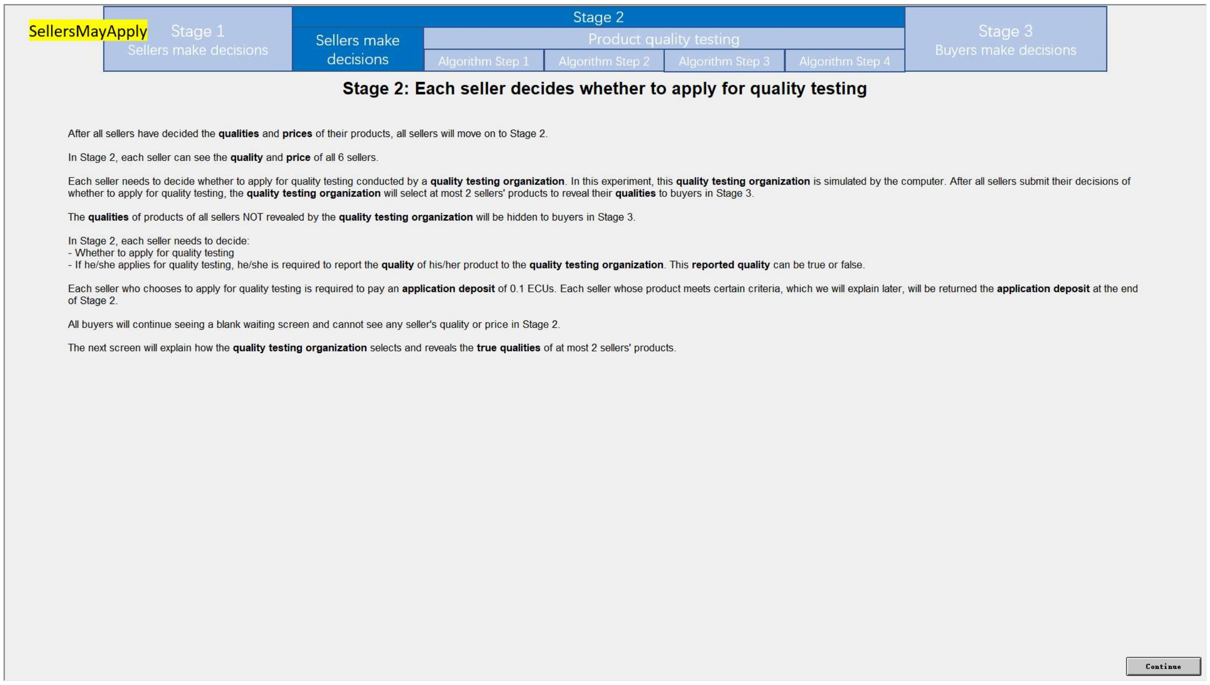
Stage 1: The quality testing organization randomly reveals the qualities of 2 sellers' products

After all sellers have decided the **quality** and **price** of their products, a **quality testing organization** will randomly select 2 sellers' products, among all 6 sellers' products, to reveal the **qualities** of these 2 sellers' products to buyers in Stage 2. The **quality testing organization** is simulated by the computer in today's experiment.

The **qualities** of the other 4 sellers' products, which are not randomly selected by the **quality testing organization**, will be hidden from buyers in Stage 2.

Continue

Figure 3.B.4. Experimental Instructions Screens 7-8



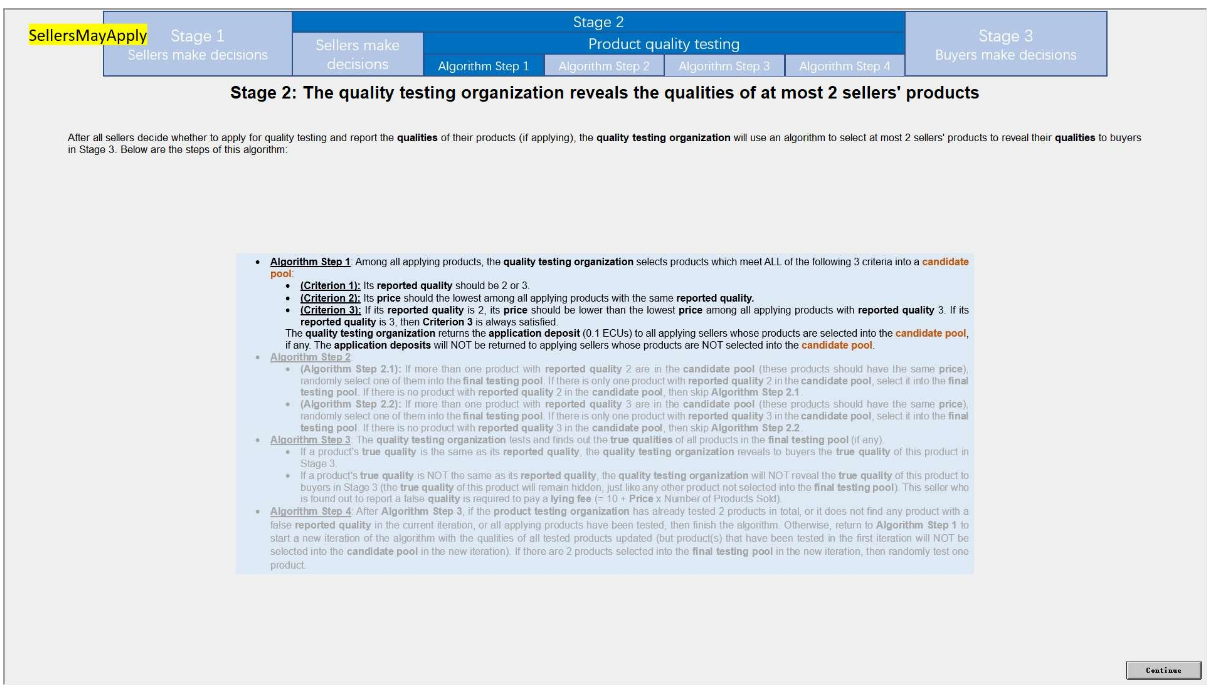
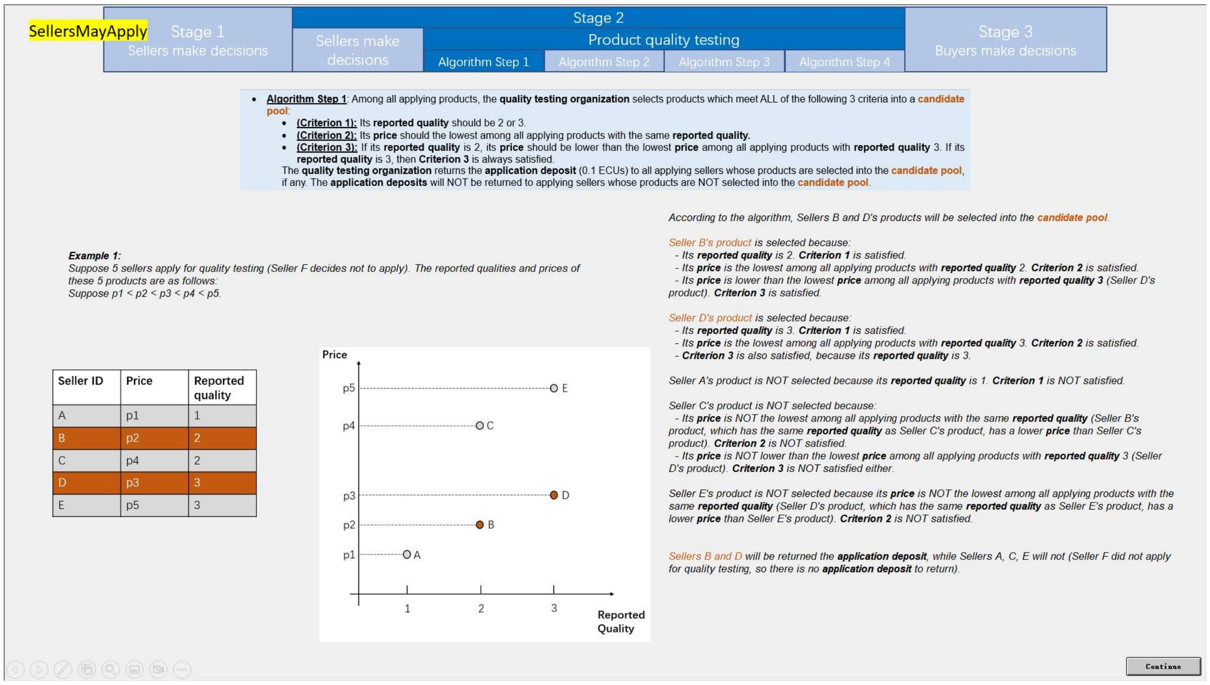


Figure 3.B.5. Experimental Instructions Screens 9-10



SellersMayApply

Stage 1 Sellers make decisions | Stage 2: Sellers make decisions; Product quality testing: Algorithm Step 1, Algorithm Step 2, Algorithm Step 3, Algorithm Step 4 | Stage 3 Buyers make decisions

- **Algorithm Step 1**: Among all applying products, the **quality testing organization** selects products which meet ALL of the following 3 criteria into a **candidate pool**:
  - **(Criterion 1):** Its **reported quality** should be 2 or 3.
  - **(Criterion 2):** Its **price** should the lowest among all applying products with the same **reported quality.**
  - **(Criterion 3):** If its **reported quality** is 2, its **price** should be lower than the lowest **price** among all applying products with **reported quality** 3. If its **reported quality** is 3, then **Criterion 3** is always satisfied.

  The **quality testing organization** returns the **application deposit** (0.1 ECUs) to all applying sellers whose products are selected into the **candidate pool**, if any. The **application deposits** will NOT be returned to applying sellers whose products are NOT selected into the **candidate pool**.

Example 1:
Suppose 5 sellers apply for quality testing (Seller F decides not to apply). The reported qualities and prices of these 5 products are as follows:
Suppose p1 < p2 < p3 < p4 < p5.

Seller ID	Price	Reported quality
A	p1	1
B	p2	2
C	p4	2
D	p3	3
E	p5	3

*According to the algorithm, Sellers B and D's products will be selected into the **candidate pool**.*

Seller B's product is selected because:
*- Its **reported quality** is 2. **Criterion 1** is satisfied.*
*- Its **price** is the lowest among all applying products with **reported quality** 2. **Criterion 2** is satisfied.*
*- Its **price** is lower than the lowest **price** among all applying products with **reported quality 3** (Seller D's product). **Criterion 3** is satisfied.*

Seller D's product is selected because:
*- Its **reported quality** is 3. **Criterion 1** is satisfied.*
*- Its **price** is the lowest among all applying products with **reported quality** 3. **Criterion 2** is satisfied.*
*- **Criterion 3** is also satisfied, because its **reported quality** is 3.*

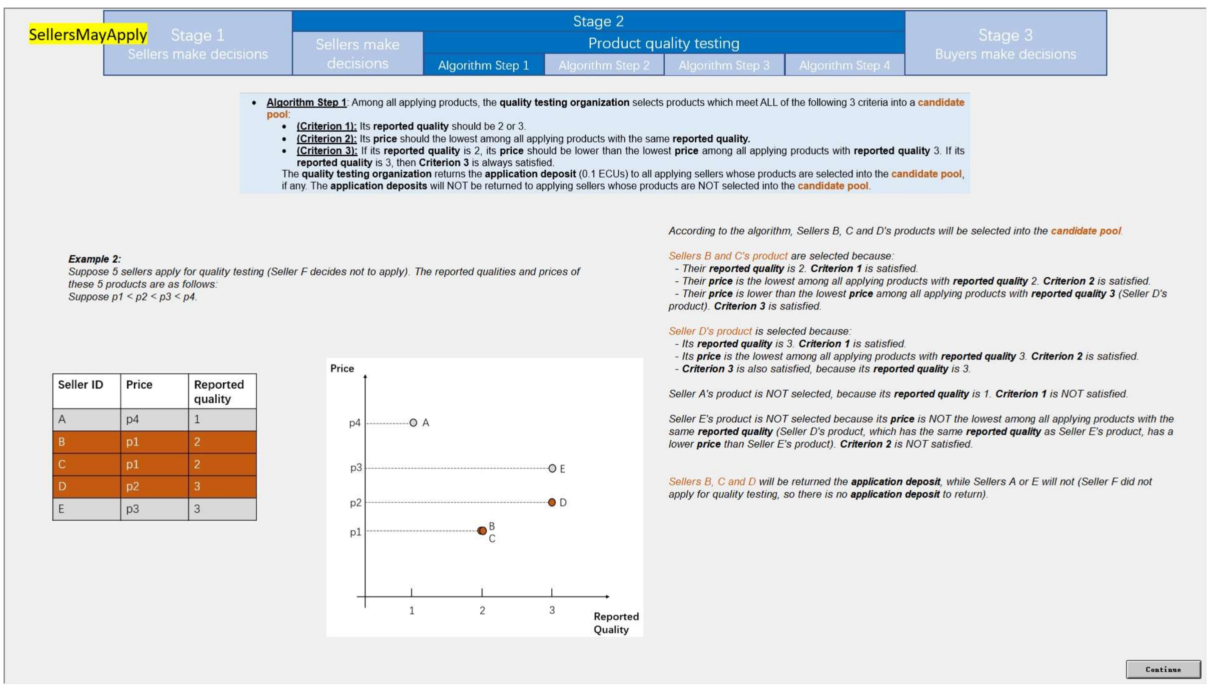
*Seller A's product is NOT selected because its **reported quality** is 1. **Criterion 1** is NOT satisfied.*

Seller C's product is NOT selected because:
*- Its **price** is NOT the lowest among all applying products with the same **reported quality** (Seller B's product, which has the same **reported quality** as Seller C's product, has a lower **price** than Seller C's product). **Criterion 2** is NOT satisfied.*
*- Its **price** is NOT lower than the lowest **price** among all applying products with **reported quality** 3 (Seller D's product). **Criterion 3** is NOT satisfied either.*

*Seller E's product is NOT selected because its **price** is NOT the lowest among all applying products with the same **reported quality** (Seller D's product, which has the same **reported quality** as Seller E's product, has a lower **price** than Seller E's product). **Criterion 2** is NOT satisfied.*

*Sellers B and D will be returned the **application deposit**, while Sellers A, C, E will not (Seller F did not apply for quality testing, so there is no **application deposit** to return).*

Continue



SellersMayApply

Stage 1 Sellers make decisions | Stage 2: Sellers make decisions; Product quality testing: Algorithm Step 1, Algorithm Step 2, Algorithm Step 3, Algorithm Step 4 | Stage 3 Buyers make decisions

- **Algorithm Step 1**: Among all applying products, the **quality testing organization** selects products which meet ALL of the following 3 criteria into a **candidate pool**:
  - **(Criterion 1):** Its **reported quality** should be 2 or 3.
  - **(Criterion 2):** Its **price** should the lowest among all applying products with the same **reported quality.**
  - **(Criterion 3):** If its **reported quality** is 2, its **price** should be lower than the lowest **price** among all applying products with **reported quality** 3. If its **reported quality** is 3, then **Criterion 3** is always satisfied.

  The **quality testing organization** returns the **application deposit** (0.1 ECUs) to all applying sellers whose products are selected into the **candidate pool**, if any. The **application deposits** will NOT be returned to applying sellers whose products are NOT selected into the **candidate pool**.

Example 2:
Suppose 5 sellers apply for quality testing (Seller F decides not to apply). The reported qualities and prices of these 5 products are as follows:
Suppose p1 < p2 < p3 < p4.

Seller ID	Price	Reported quality
A	p4	1
B	p1	2
C	p1	2
D	p2	3
E	p3	3

*According to the algorithm, Sellers B, C and D's products will be selected into the **candidate pool**.*

Sellers B and C's product are selected because:
*- Their **reported quality** is 2. **Criterion 1** is satisfied.*
*- Their **price** is the lowest among all applying products with **reported quality** 2. **Criterion 2** is satisfied.*
*- Their **price** is lower than the lowest **price** among all applying products with **reported quality 3** (Seller D's product). **Criterion 3** is satisfied.*

Seller D's product is selected because:
*- Its **reported quality** is 3. **Criterion 1** is satisfied.*
*- Its **price** is the lowest among all applying products with **reported quality** 3. **Criterion 2** is satisfied.*
*- **Criterion 3** is also satisfied, because its **reported quality** is 3.*

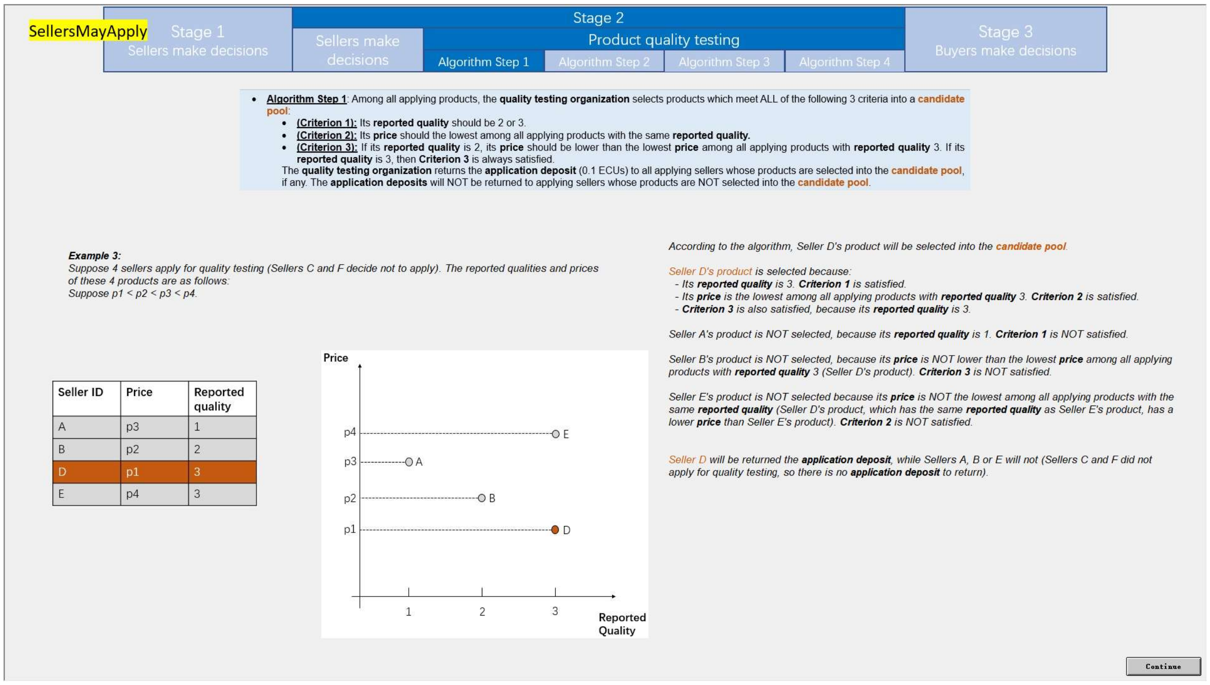
*Seller A's product is NOT selected, because its **reported quality** is 1. **Criterion 1** is NOT satisfied.*

*Seller E's product is NOT selected because its **price** is NOT the lowest among all applying products with the same **reported quality** (Seller D's product, which has the same **reported quality** as Seller E's product, has a lower **price** than Seller E's product). **Criterion 2** is NOT satisfied.*

*Sellers B, C and D will be returned the **application deposit**, while Sellers A or E will not (Seller F did not apply for quality testing, so there is no **application deposit** to return).*

Continue

Figure 3.B.6. Experimental Instructions Screens 11-12



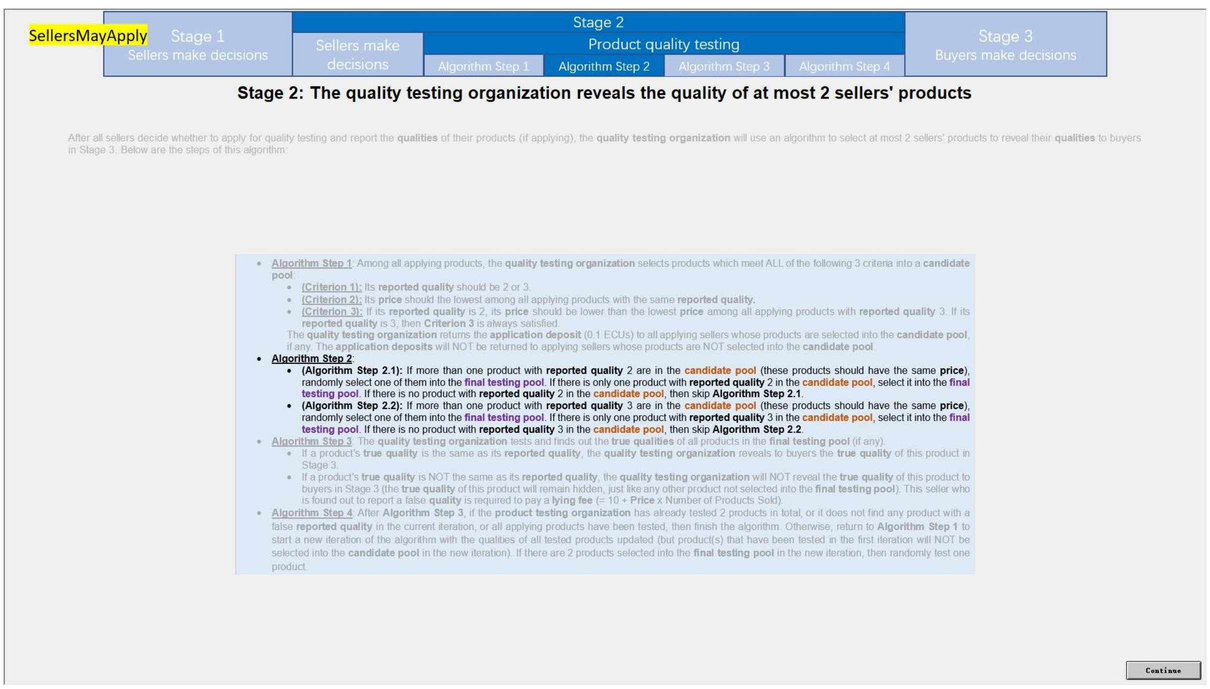
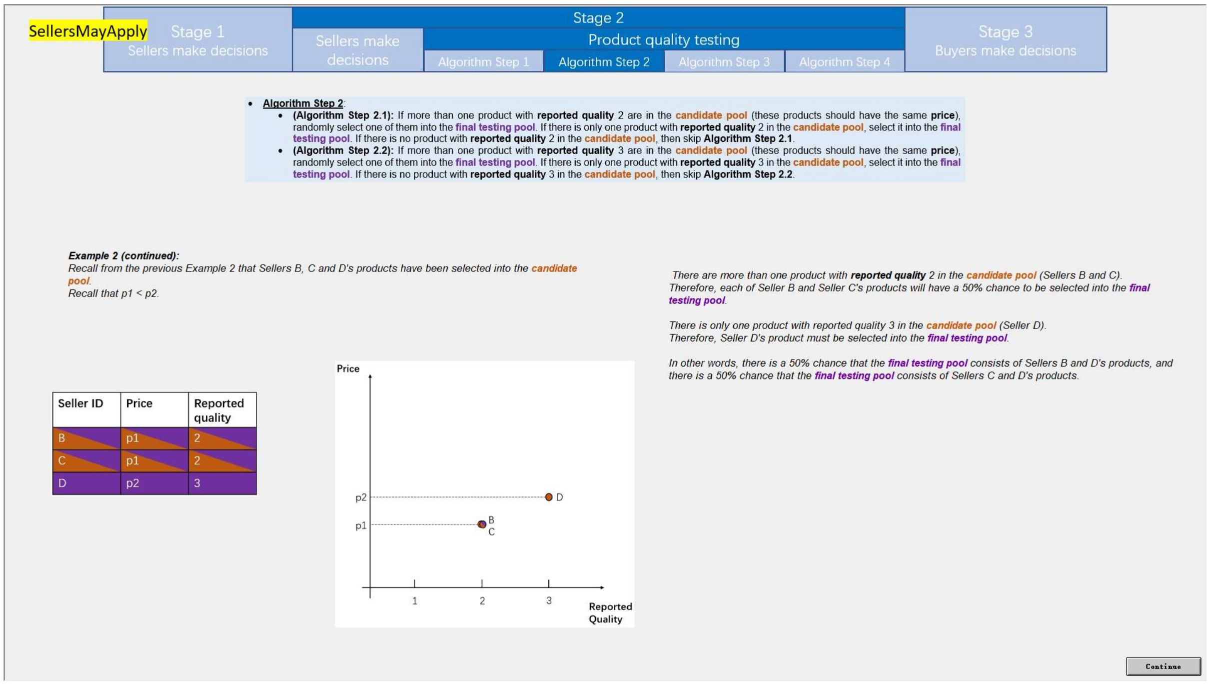


Figure 3.B.7. Experimental Instructions Screens 13-14



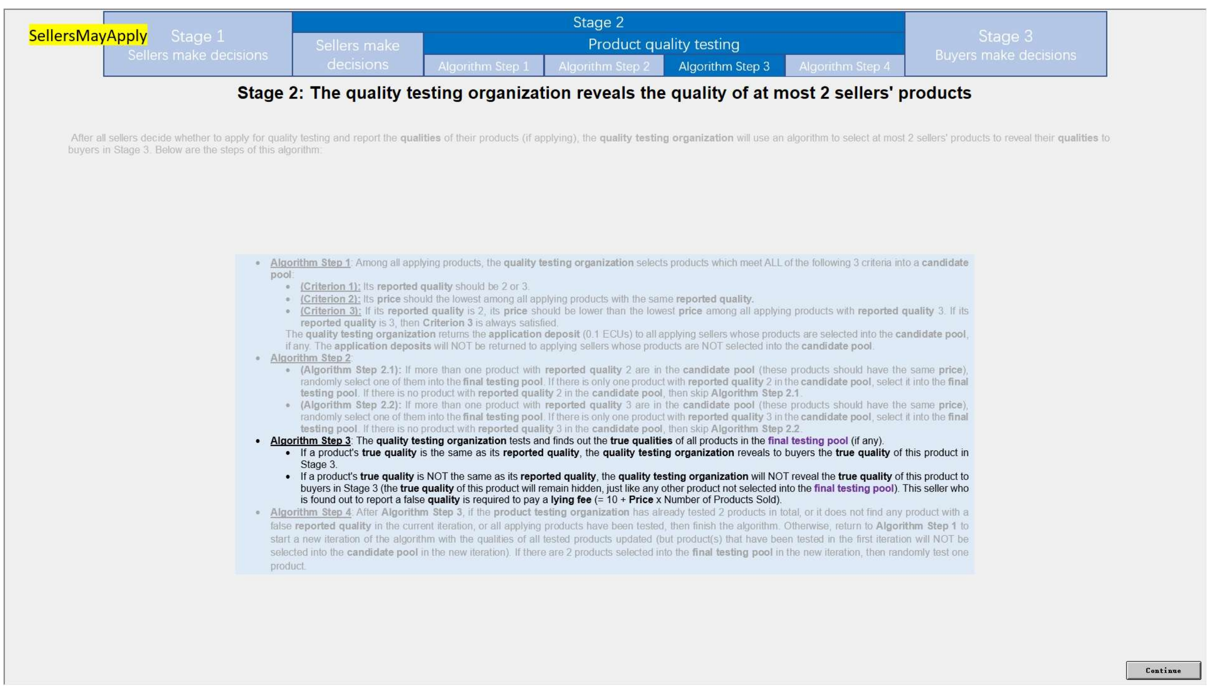
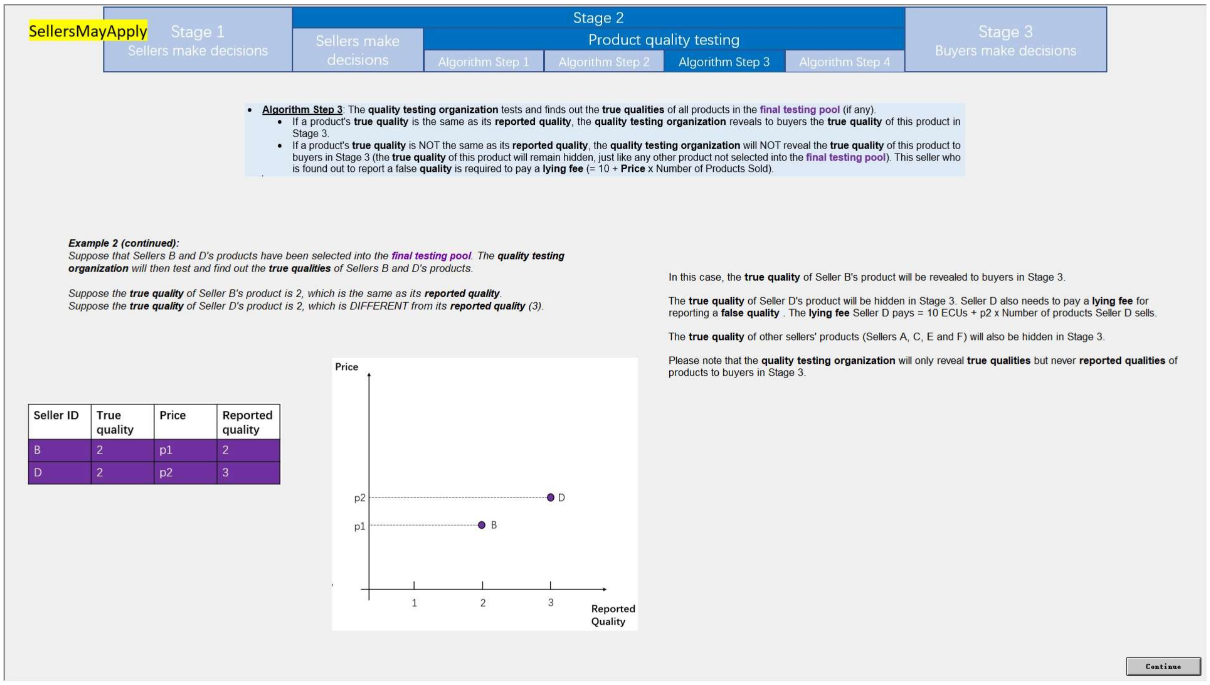


Figure 3.B.8. Experimental Instructions Screens 15-16



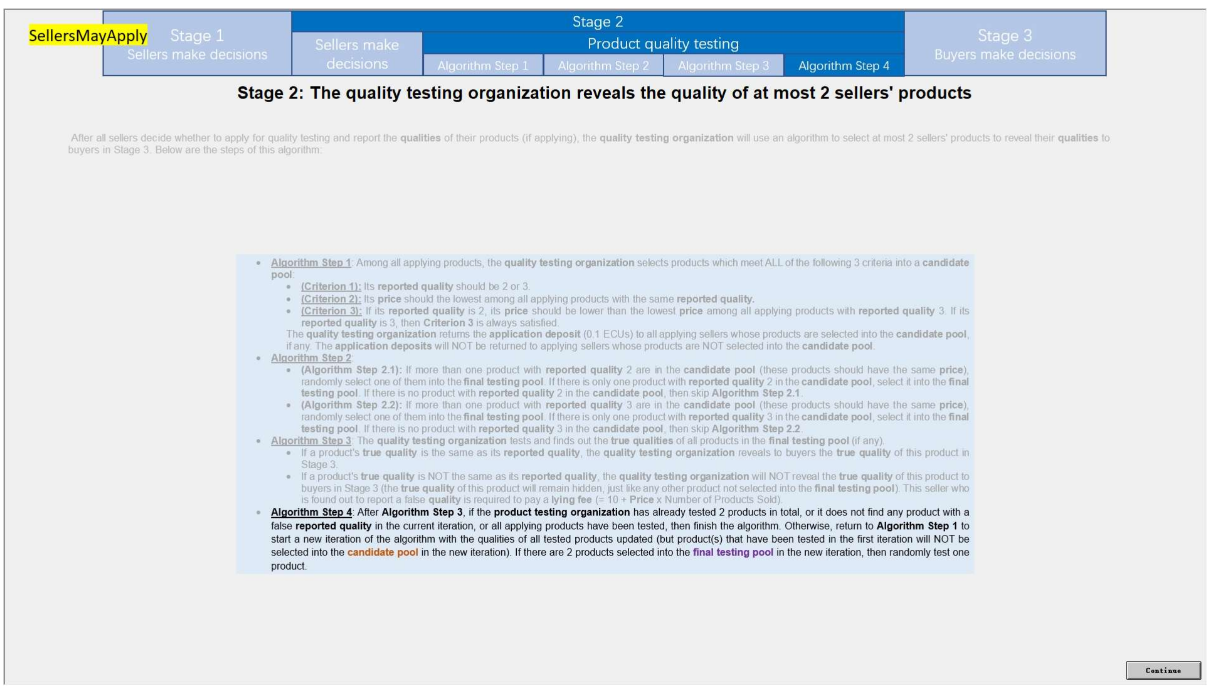
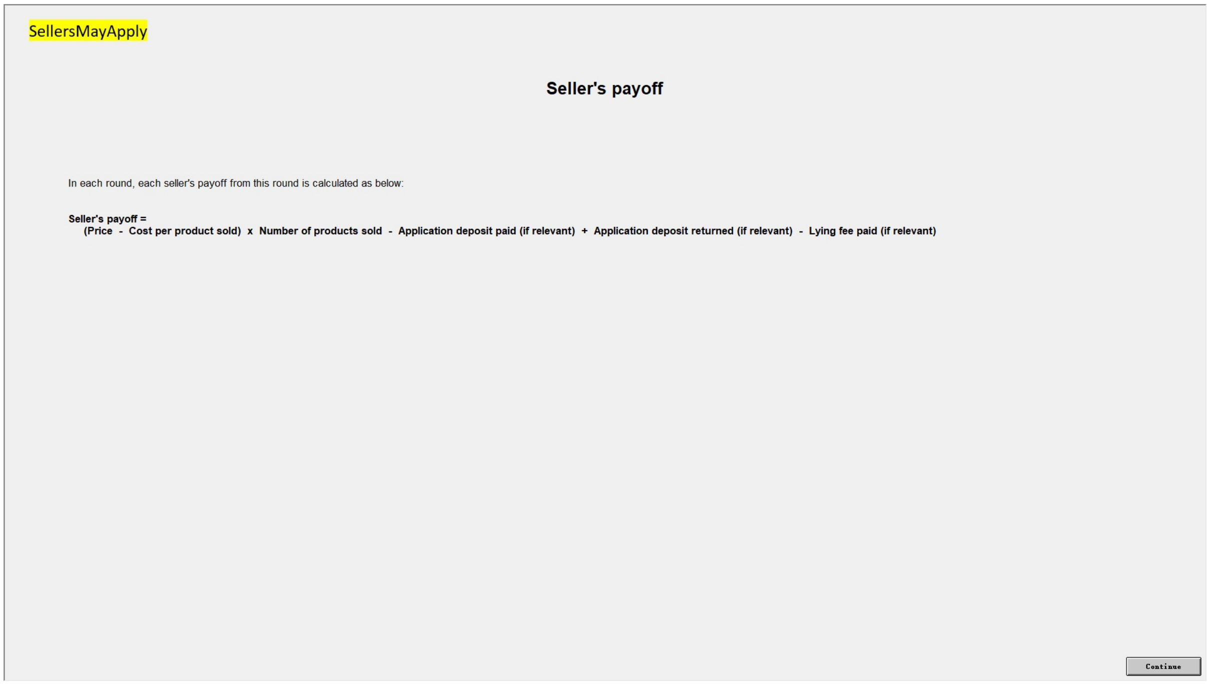


Figure 3.B.9. Experimental Instructions Screens 17-18



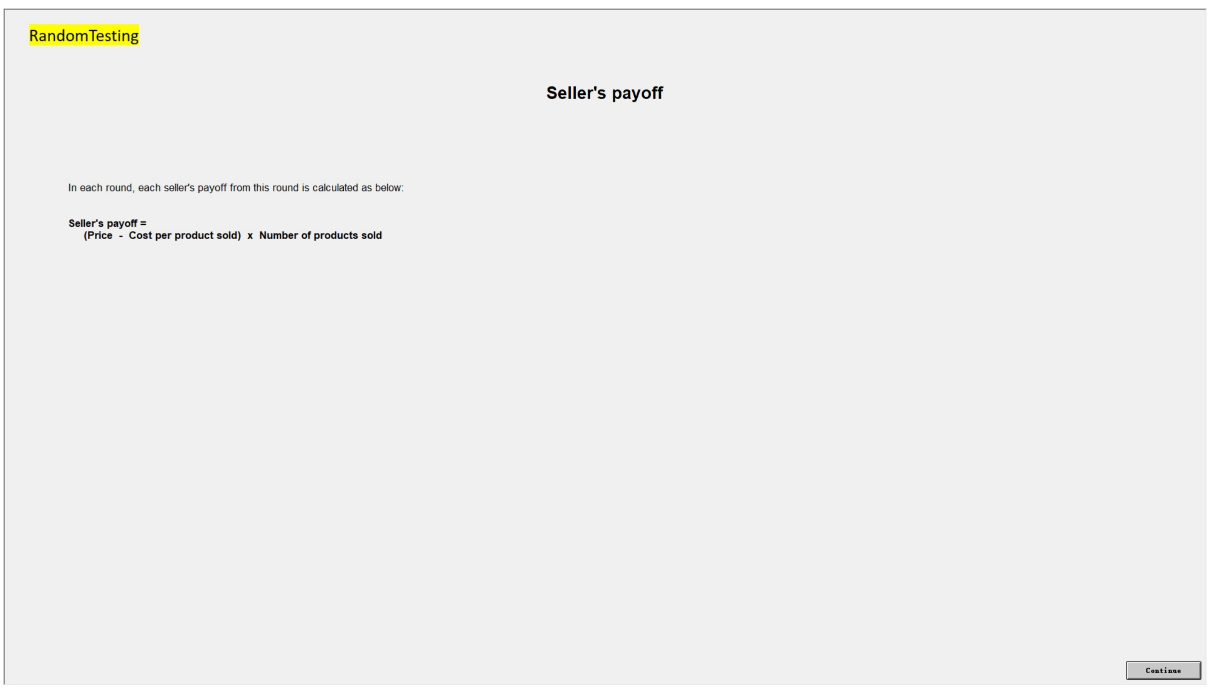
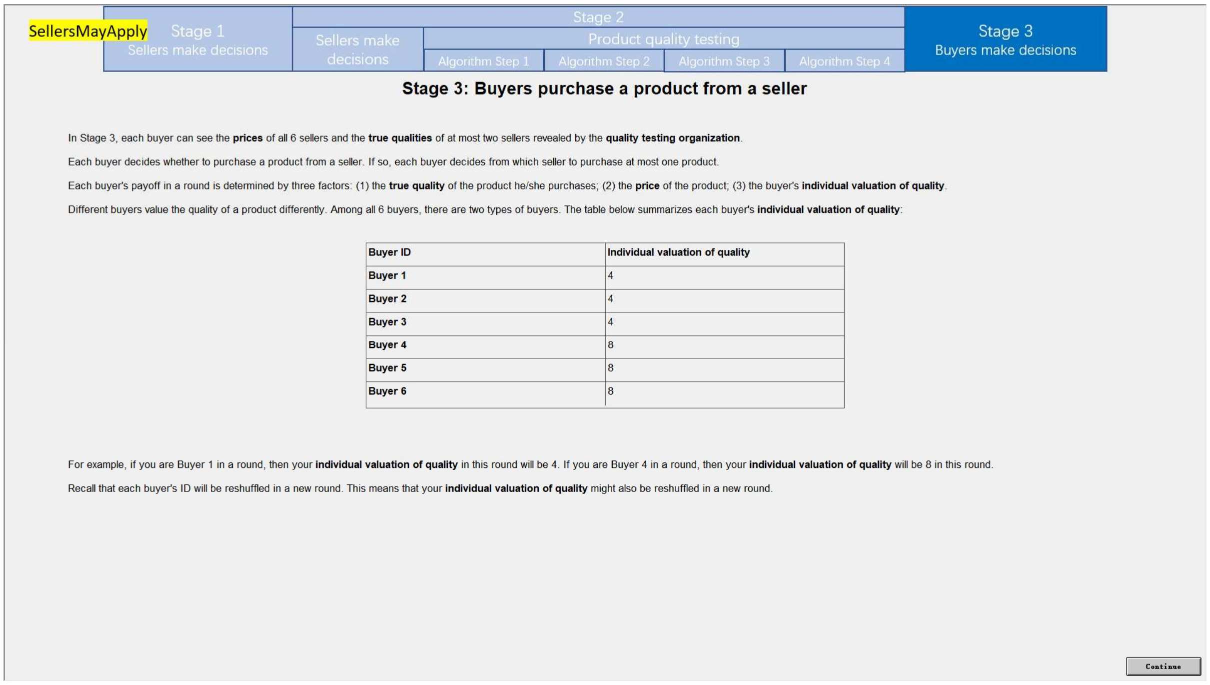


Figure 3.B.10. Experimental Instructions Screens 19-20



SellersMayApply

Stage 1 Sellers make decisions | Stage 2: Sellers make decisions; Product quality testing: Algorithm Step 1, Algorithm Step 2, Algorithm Step 3, Algorithm Step 4 | Stage 3 Buyers make decisions

Stage 3: Buyers purchase a product from a seller

In Stage 3, each buyer can see the **prices** of all 6 sellers and the **true qualities** of at most two sellers revealed by the **quality testing organization**.

Each buyer decides whether to purchase a product from a seller. If so, each buyer decides from which seller to purchase at most one product.

Each buyer's payoff in a round is determined by three factors: (1) the **true quality** of the product he/she purchases; (2) the **price** of the product; (3) the buyer's **individual valuation of quality**.

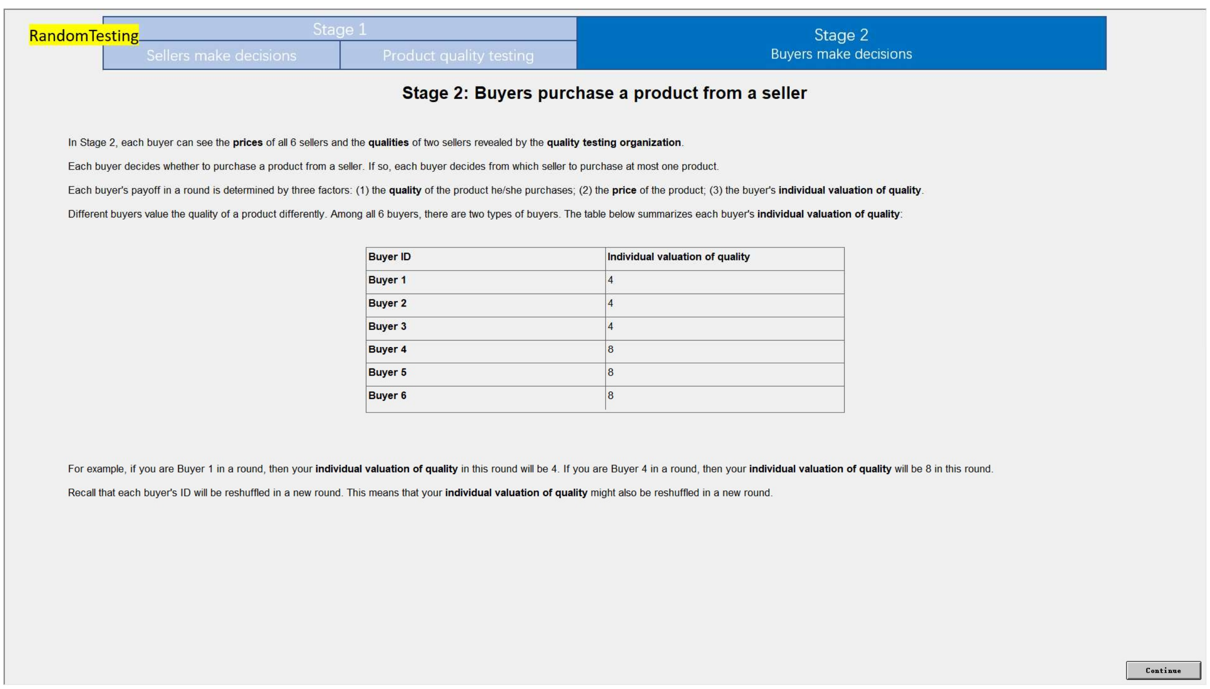
Different buyers value the quality of a product differently. Among all 6 buyers, there are two types of buyers. The table below summarizes each buyer's **individual valuation of quality**:

Buyer ID	**Individual valuation of quality**
Buyer 1	4
Buyer 2	4
Buyer 3	4
Buyer 4	8
Buyer 5	8
Buyer 6	8

For example, if you are Buyer 1 in a round, then your **individual valuation of quality** in this round will be 4. If you are Buyer 4 in a round, then your **individual valuation of quality** will be 8 in this round.

Recall that each buyer's ID will be reshuffled in a new round. This means that your **individual valuation of quality** might also be reshuffled in a new round.

Continue



RandomTesting

Stage 1: Sellers make decisions; Product quality testing | Stage 2 Buyers make decisions

Stage 2: Buyers purchase a product from a seller

In Stage 2, each buyer can see the **prices** of all 6 sellers and the **qualities** of two sellers revealed by the **quality testing organization**.

Each buyer decides whether to purchase a product from a seller. If so, each buyer decides from which seller to purchase at most one product.

Each buyer's payoff in a round is determined by three factors: (1) the **quality** of the product he/she purchases; (2) the **price** of the product; (3) the buyer's **individual valuation of quality**.

Different buyers value the quality of a product differently. Among all 6 buyers, there are two types of buyers. The table below summarizes each buyer's **individual valuation of quality**:

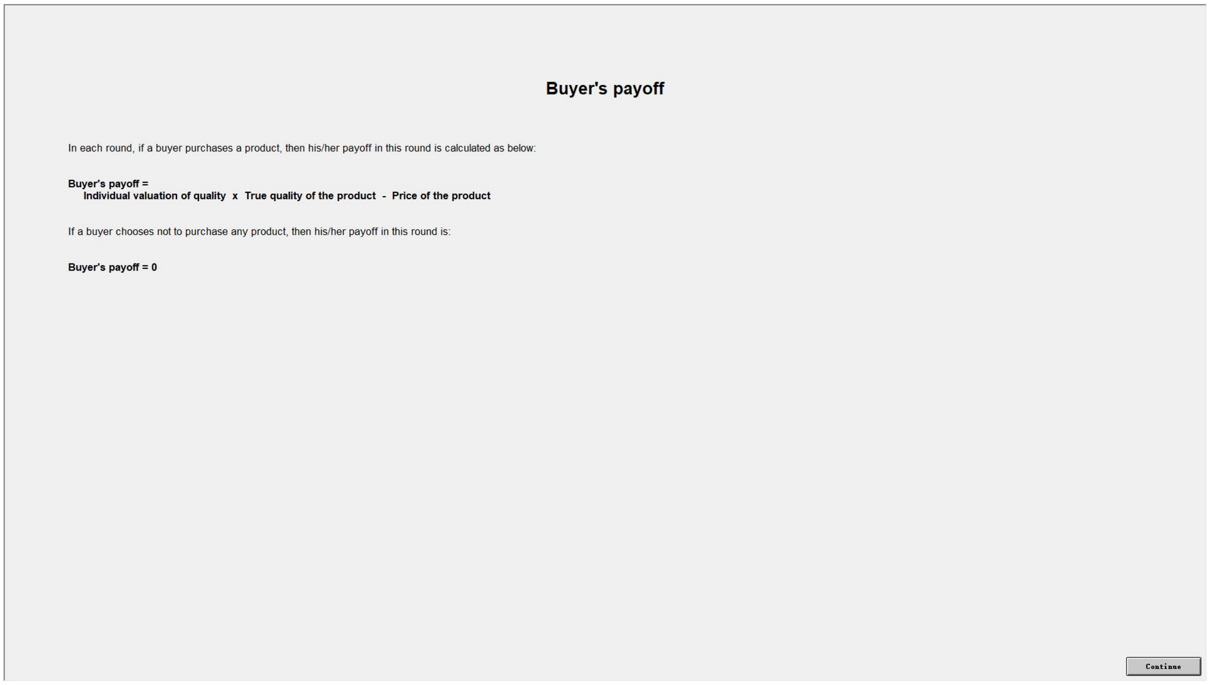
Buyer ID	**Individual valuation of quality**
Buyer 1	4
Buyer 2	4
Buyer 3	4
Buyer 4	8
Buyer 5	8
Buyer 6	8

For example, if you are Buyer 1 in a round, then your **individual valuation of quality** in this round will be 4. If you are Buyer 4 in a round, then your **individual valuation of quality** will be 8 in this round.

Recall that each buyer's ID will be reshuffled in a new round. This means that your **individual valuation of quality** might also be reshuffled in a new round.

Continue

Figure 3.B.11. Experimental Instructions Screens 21-22


Buyer's payoff

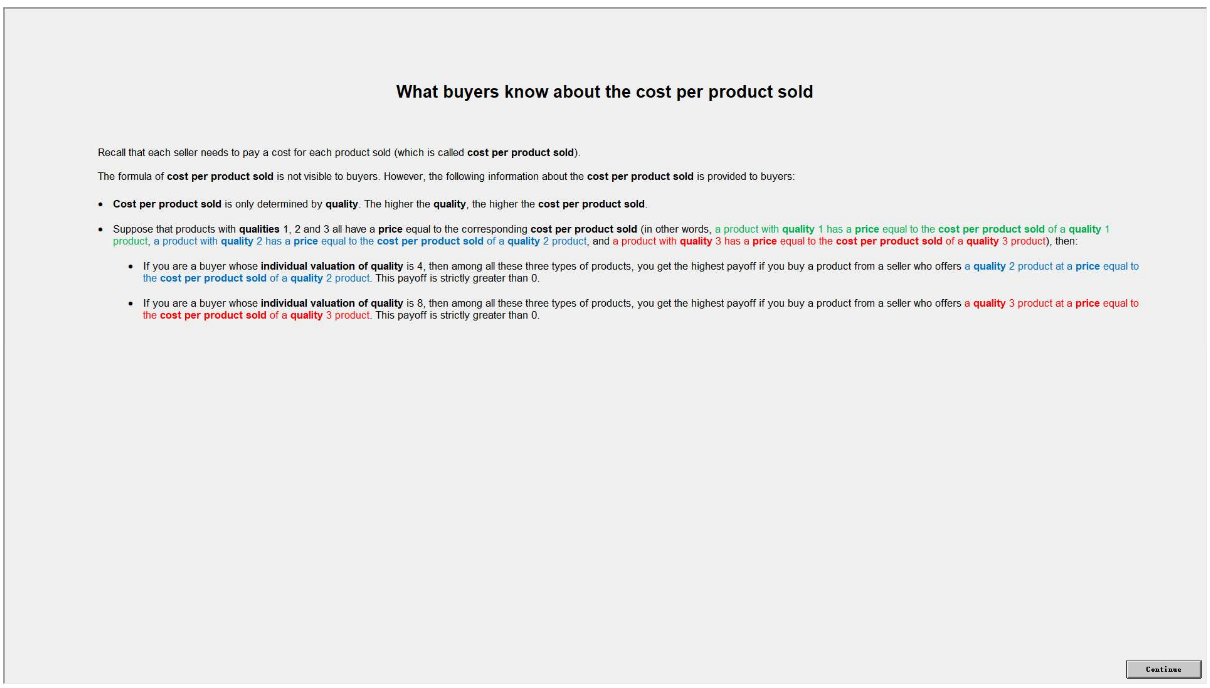
In each round, if a buyer purchases a product, then his/her payoff in this round is calculated as below:

Buyer's payoff =
Individual valuation of quality x True quality of the product - Price of the product

If a buyer chooses not to purchase any product, then his/her payoff in this round is:

Buyer's payoff = 0

Continue


What buyers know about the cost per product sold

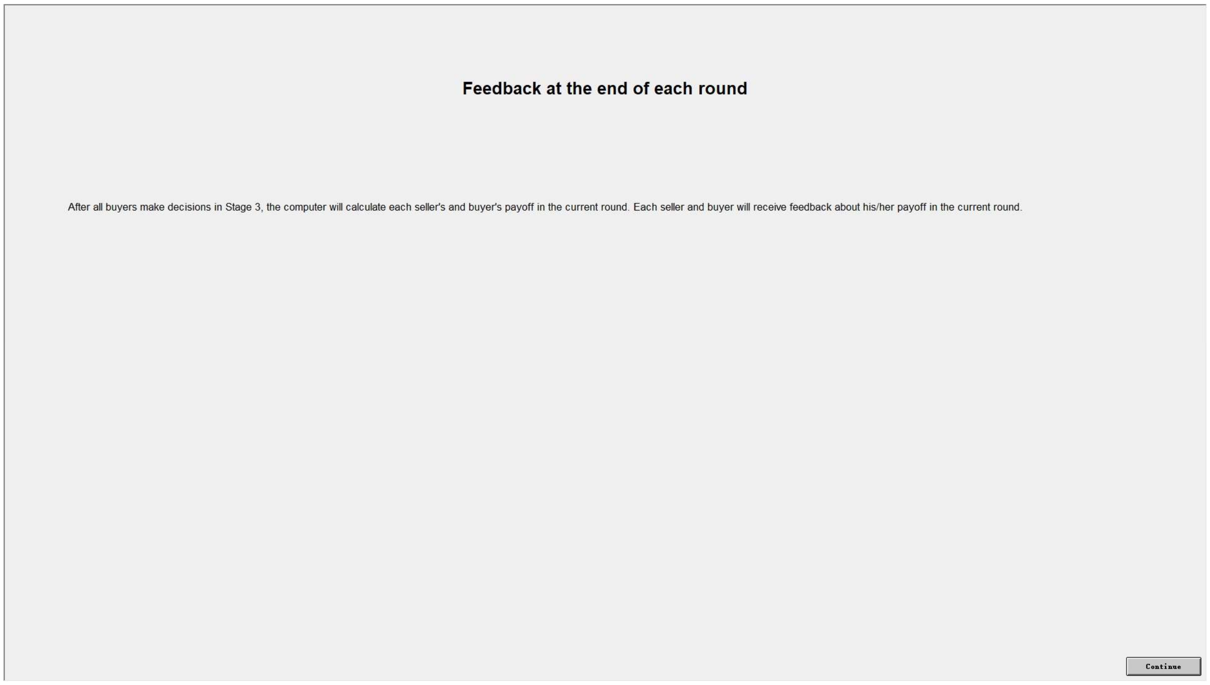
Recall that each seller needs to pay a cost for each product sold (which is called **cost per product sold**).

The formula of **cost per product sold** is not visible to buyers. However, the following information about the **cost per product sold** is provided to buyers:

- **Cost per product sold** is only determined by **quality**. The higher the **quality**, the higher the **cost per product sold**.
- Suppose that products with **qualities** 1, 2 and 3 all have a **price** equal to the corresponding **cost per product sold** (in other words, a product with **quality** 1 has a **price** equal to the **cost per product sold** of a **quality** 1 product, a product with **quality** 2 has a **price** equal to the **cost per product sold** of a **quality** 2 product, and a product with **quality** 3 has a **price** equal to the **cost per product sold** of a **quality** 3 product), then:
  - If you are a buyer whose **individual valuation of quality** is 4, then among all these three types of products, you get the highest payoff if you buy a product from a seller who offers a **quality** 2 product at a **price** equal to the **cost per product sold** of a **quality** 2 product. This payoff is strictly greater than 0.
  - If you are a buyer whose **individual valuation of quality** is 8, then among all these three types of products, you get the highest payoff if you buy a product from a seller who offers a **quality** 3 product at a **price** equal to the **cost per product sold** of a **quality** 3 product. This payoff is strictly greater than 0.

Continue

Figure 3.B.12. Experimental Instructions Screens 23-24



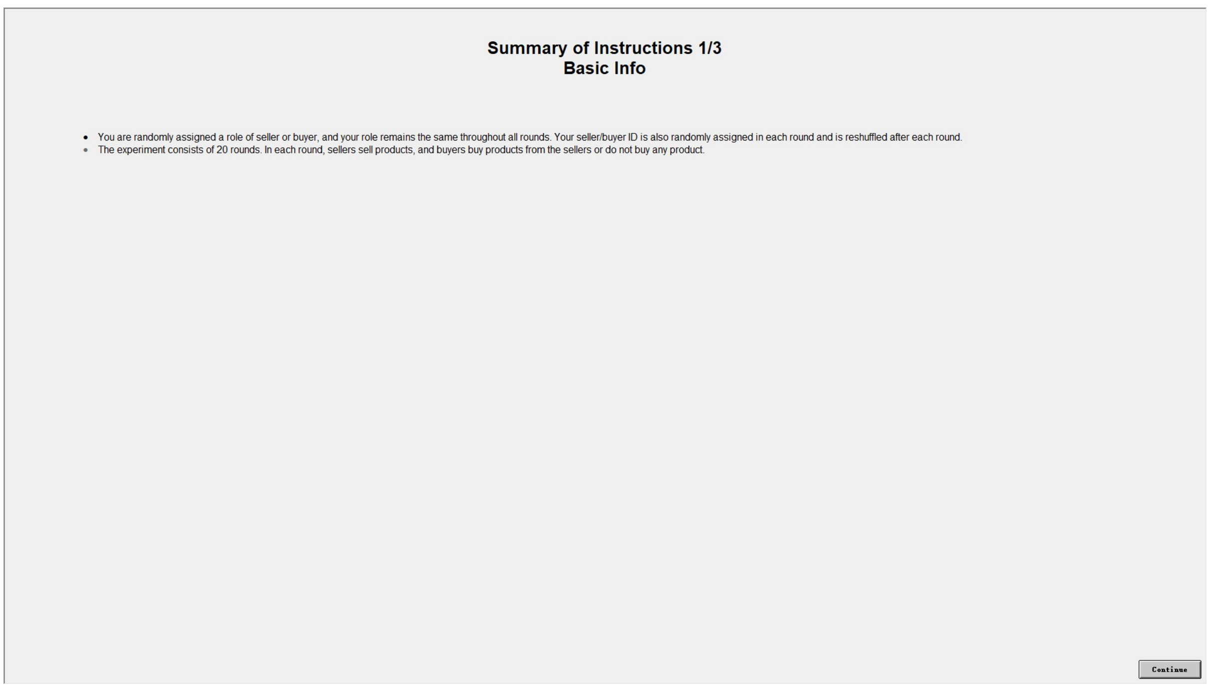


Figure 3.B.13. Experimental Instructions Screens 25-26

SellersMayApply

Summary of Instructions 2/3
Procedures

	Stage 1	Stage 2	Stage 3

Sellers	Each seller decides the **quality** and **price** of his/her product.	• Each seller sees the **qualities** and **prices** of all 6 sellers' products.
		• Each seller decides whether to apply for quality testing.
		  ◦ If a seller applies for quality testing, he/she pays an **application deposit** of 0.1 ECUs (this **application deposit** will be returned to the seller if his/her product is selected into the **candidate pool**).
		  ◦ If a seller applies for quality testing, he/she needs to report the **quality** of his/her products to the **quality testing organization** (a seller can report a false **quality**, but the seller needs to pay a **lying fee** (= 10 + **Price** x Number of Products Sold) if his/her product with a false **reported quality** is tested, and the **true quality** of this product will not be revealed to buyers in Stage 3).
			Waiting for buyers to make decisions.

Buyers	Waiting for sellers to make decisions.	Waiting for sellers to make decisions.	• Each buyer sees the **price** of each seller. Each buyer sees the **true qualities** of at most 2 sellers' products revealed by the **quality testing organization**. The **true qualities** of other products are hidden. • Each buyer decides from which seller to purchase one product. Each buyer can also decide not to purchase any product.

Quality Testing Organization
 	
(Simulated by the computer)
		After all sellers decide whether to apply for quality testing and report the **quality** of their products (if applying), the **quality testing organization** will use an algorithm to select at most 2 sellers' products to reveal their **true qualities** to buyers in Stage 3. The algorithm consists of 3 steps:
		• **Algorithm Step 1**: Among all applying products, the **quality testing organization** selects products which meet ALL of the following 3 criteria into a **candidate pool**:
		  ◦ **(Criterion 1):** Its **reported quality** should be 2 or 3.
		  ◦ **(Criterion 2):** Its **price** should the lowest among all applying products with the same **reported quality.**
		  ◦ **(Criterion 3):** If its **reported quality** is 2, its **price** should be lower than the lowest **price** among all applying products with **reported quality** 3. If its **reported quality** is 3, then **Criterion 3** is always satisfied.
		  The **quality testing organization** returns the **application deposit** (0.1 ECUs) to all applying sellers whose products are selected into the **candidate pool**, if any. The **application deposits** will NOT be returned to applying sellers whose products are NOT selected into the **candidate pool**.
		• **Algorithm Step 2**:
		  ◦ **(Algorithm Step 2.1):** If more than one product with **reported quality** 2 are in the **candidate pool** (these products should have the same **price**), randomly select one of them into the **final testing pool**. If there is only one product with **reported quality** 2 in the **candidate pool**, select it into the **final testing pool**. If there is no product with **reported quality** 2 in the **candidate pool**, then skip **Algorithm Step 2.1**.
		  ◦ **(Algorithm Step 2.2):** If more than one product with **reported quality** 3 are in the **candidate pool** (these products should have the same **price**), randomly select one of them into the **final testing pool**. If there is only one product with **reported quality** 3 in the **candidate pool**, select it into the **final testing pool**. If there is no product with **reported quality** 3 in the **candidate pool**, then skip **Algorithm Step 2.2**.
		• **Algorithm Step 3**: The **quality testing organization** tests and finds out the **true qualities** of all products in the **final testing pool** (if any).
		  ◦ If a product's **true quality** is the same as its **reported quality**, the **quality testing organization** reveals to buyers the **true quality** of this product in Stage 3.
		  ◦ If a product's **true quality** is NOT the same as its **reported quality**, the **quality testing organization** will NOT reveal the **true quality** of this product to buyers in Stage 3 (the **true quality** of this product will remain hidden, just like any other product not selected into the **final testing pool**). This seller who is found out to report a false **quality** is required to pay a **lying fee** (= 10 + **Price** x Number of Products Sold).
		• **Algorithm Step 4**: After **Algorithm Step 3**, if the **product testing organization** has already tested 2 products in total, or it does not find any product with a false **reported quality** in the current iteration, or all applying products have been tested, then finish the algorithm. Otherwise, return to **Algorithm Step 1** to start a new iteration of the algorithm with the qualities of all tested products updated (but product(s) that have been tested in the first iteration will NOT be selected into the **candidate pool** in the new iteration). If there are 2 products selected into the **final testing pool** in the new iteration, then randomly test one product.	

Continue

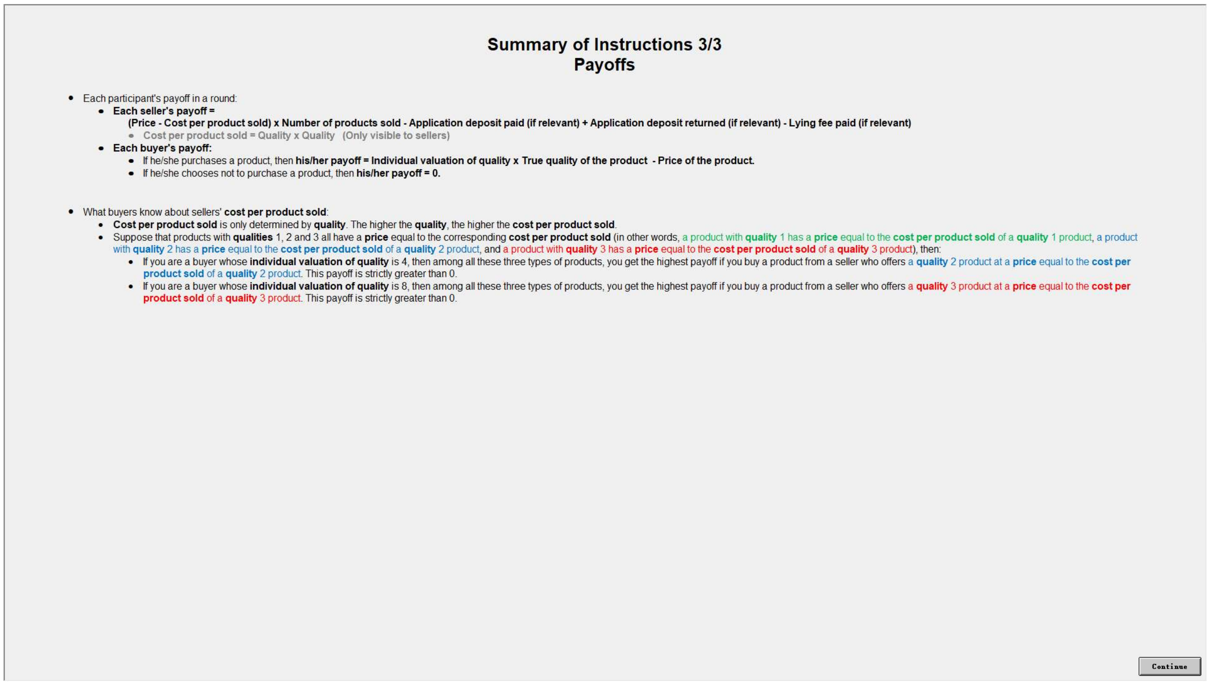
RandomTesting

Summary of Instructions 2/3
Procedures

	Stage 1	Stage 2
Sellers	Each seller decides the **quality** and **price** of his/her product.	Waiting for buyers to make decisions.
Buyers	Waiting for sellers to make decisions.	• Each buyer sees the **price** of each seller. Each buyer sees the **qualities** of the 2 sellers' products revealed by the **quality testing organization**. The **qualities** of other products are hidden. • Each buyer decides from which seller to purchase one product. Each buyer can also decide not to purchase any product.
Quality Testing Organization (Simulated by the computer)	After all sellers decide the **qualities** and **prices** of their products, the **quality testing organization** will randomly select 2 sellers' products to reveal their **qualities** to buyers in Stage 2. The **qualities** of all the other 4 sellers' products that are NOT randomly selected will be hidden from buyers in Stage 2.	

Continue

Figure 3.B.14. Experimental Instructions Screens 27-28



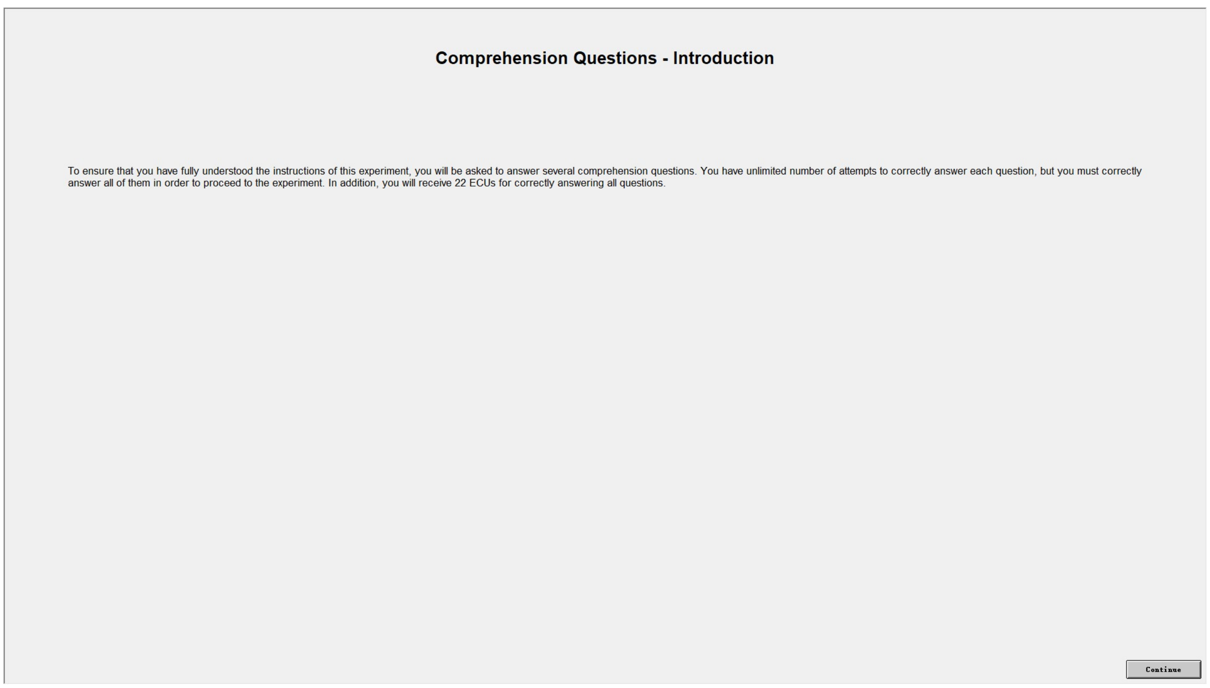
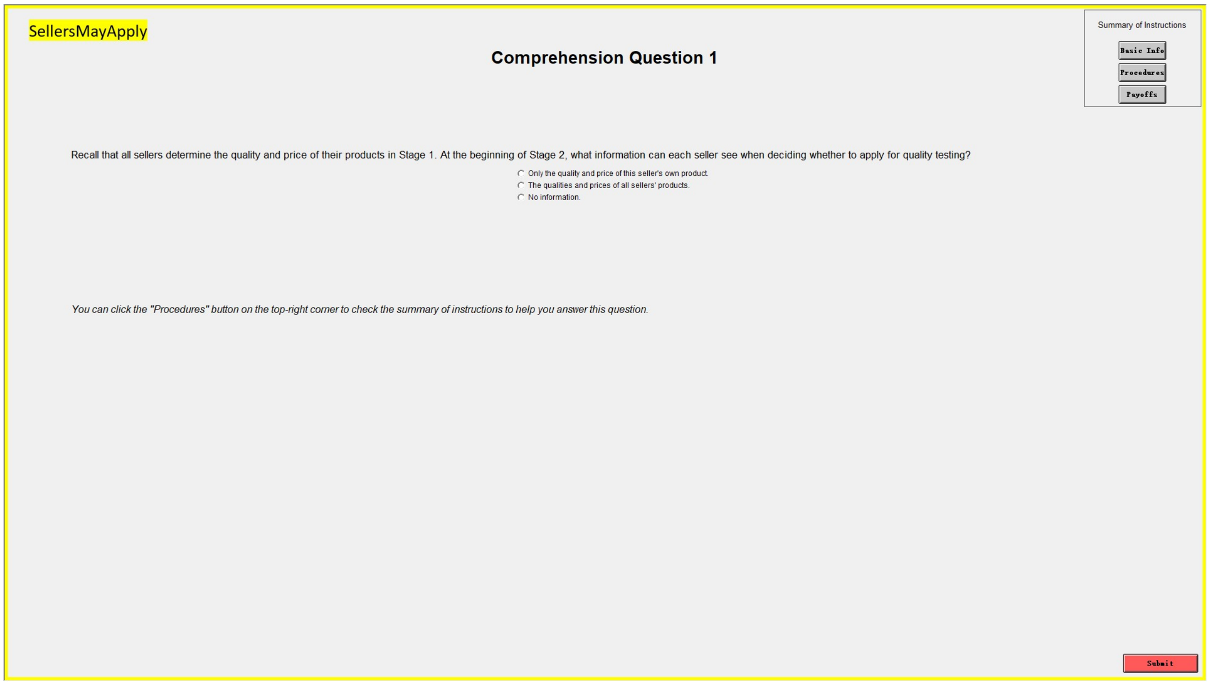


Figure 3.B.15. Experimental Instructions Screens 29-30



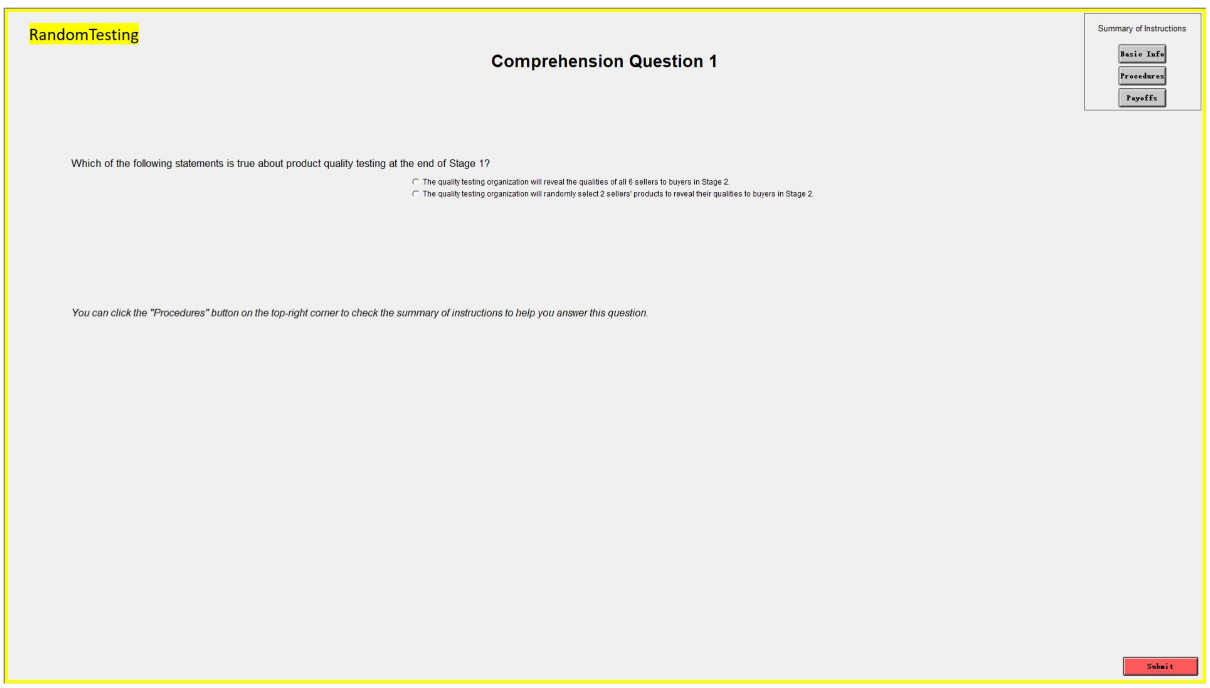
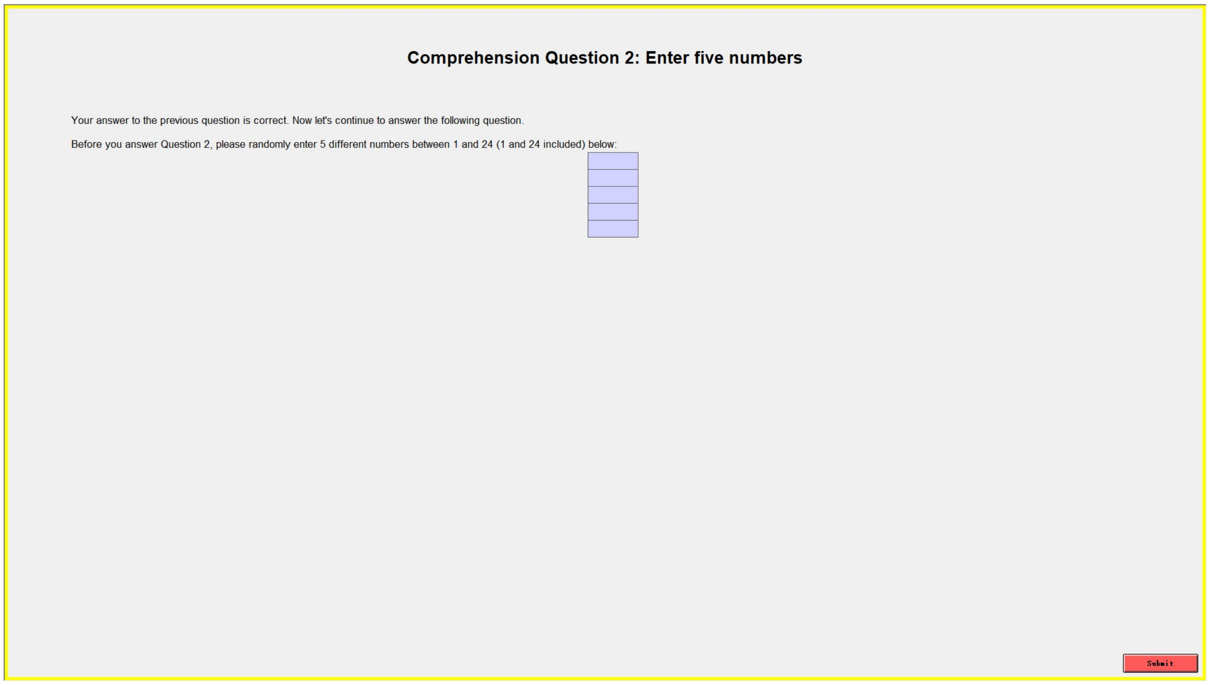


Figure 3.B.16. Experimental Instructions Screens 31-32



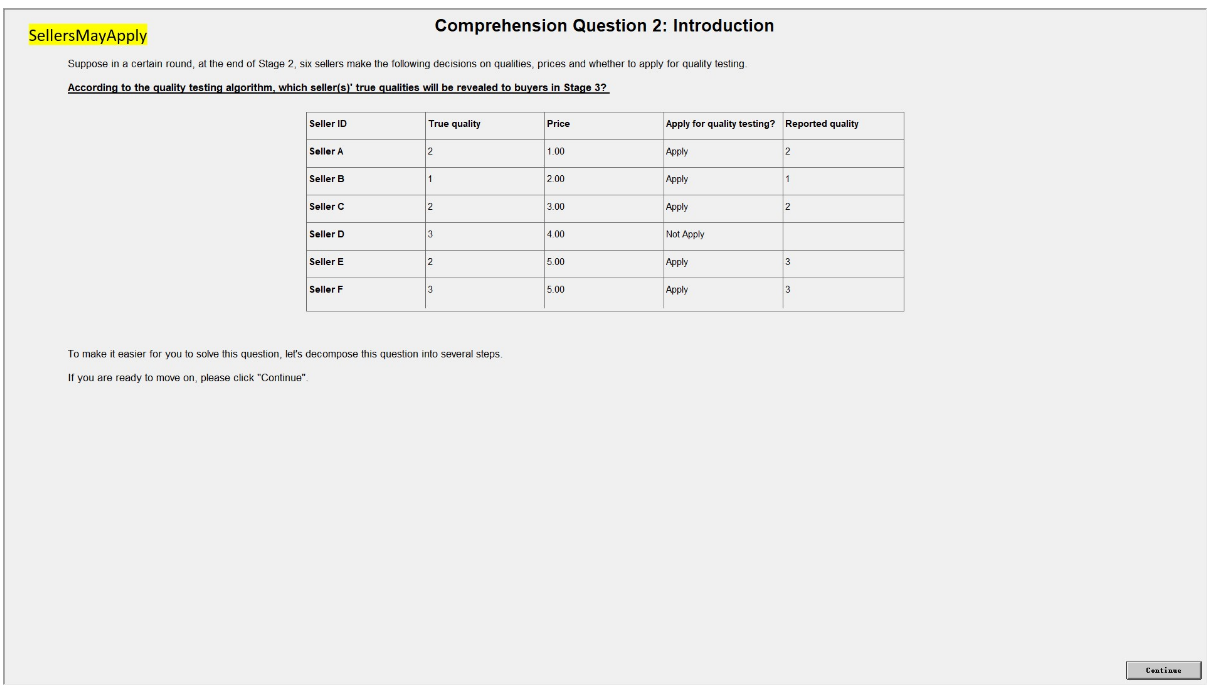
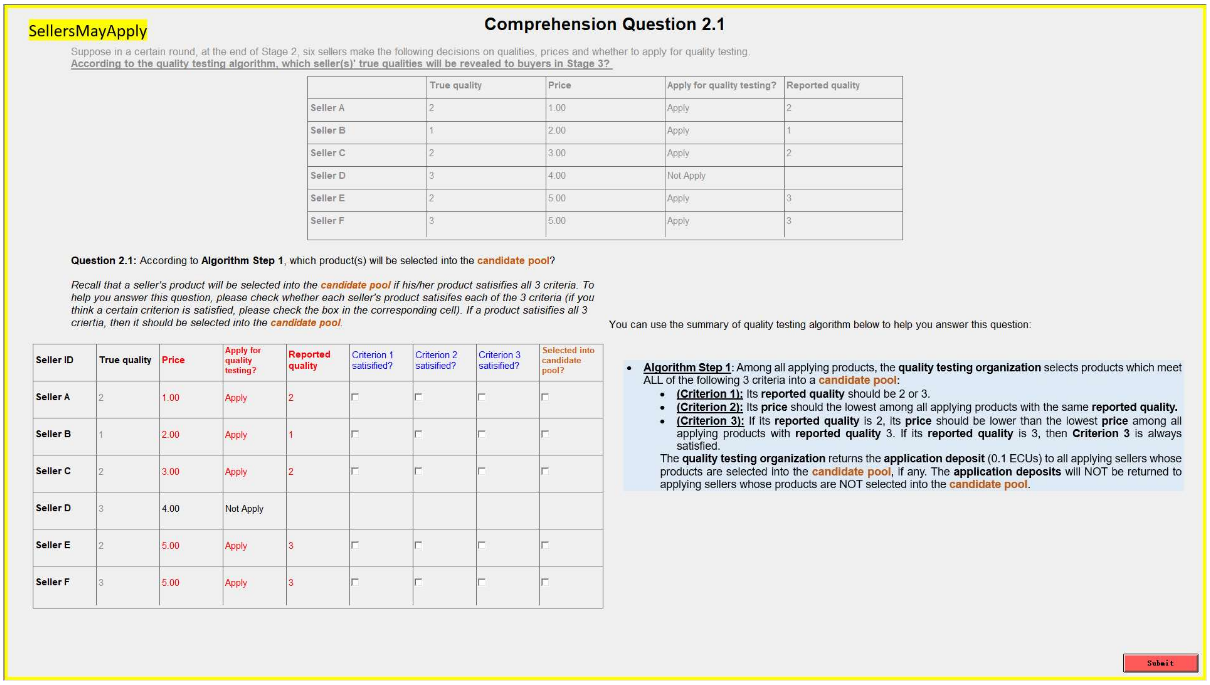


Figure 3.B.17. Experimental Instructions Screens 33-34



SellersMayApply

Comprehension Question 2.1

Suppose in a certain round, at the end of Stage 2, six sellers make the following decisions on qualities, prices and whether to apply for quality testing.
According to the quality testing algorithm, which seller(s)' true qualities will be revealed to buyers in Stage 3?

	True quality	Price	Apply for quality testing?	Reported quality
Seller A	2	1.00	Apply	2
Seller B	1	2.00	Apply	1
Seller C	2	3.00	Apply	2
Seller D	3	4.00	Not Apply	
Seller E	2	5.00	Apply	3
Seller F	3	5.00	Apply	3

Question 2.1: According to **Algorithm Step 1**, which product(s) will be selected into the **candidate pool**?

*Recall that a seller's product will be selected into the **candidate pool** if his/her product satisifies all 3 criteria. To help you answer this question, please check whether each seller's product satisifes each of the 3 criteria (if you think a certain criterion is satisfied, please check the box in the corresponding cell). If a product satisifies all 3 criertia, then it should be selected into the **candidate pool**.*

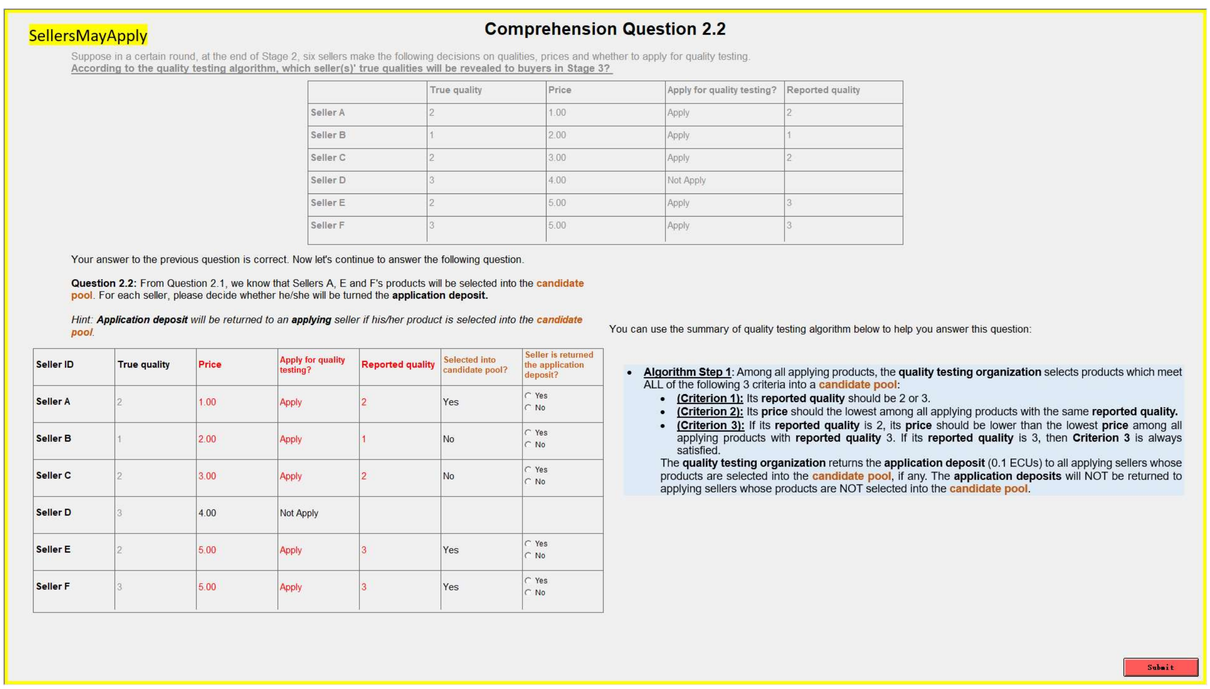
Seller ID	True quality	Price	Apply for quality testing?	Reported quality	Criterion 1 satisified?	Criterion 2 satisified?	Criterion 3 satisified?	Selected into candidate pool?
Seller A	2	1.00	Apply	2	☐	☐	☐	☐
Seller B	1	2.00	Apply	1	☐	☐	☐	☐
Seller C	2	3.00	Apply	2	☐	☐	☐	☐
Seller D	3	4.00	Not Apply					
Seller E	2	5.00	Apply	3	☐	☐	☐	☐
Seller F	3	5.00	Apply	3	☐	☐	☐	☐

You can use the summary of quality testing algorithm below to help you answer this question:

- **Algorithm Step 1**: Among all applying products, the **quality testing organization** selects products which meet ALL of the following 3 criteria into a **candidate pool**:
  - **(Criterion 1):** Its **reported quality** should be 2 or 3.
  - **(Criterion 2):** Its **price** should the lowest among all applying products with the same **reported quality.**
  - **(Criterion 3):** If its **reported quality** is 2, its **price** should be lower than the lowest **price** among all applying products with **reported quality** 3. If its **reported quality** is 3, then **Criterion 3** is always satisfied.

  The **quality testing organization** returns the **application deposit** (0.1 ECUs) to all applying sellers whose products are selected into the **candidate pool**, if any. The **application deposits** will NOT be returned to applying sellers whose products are NOT selected into the **candidate pool**.

Submit



SellersMayApply

Comprehension Question 2.2

Suppose in a certain round, at the end of Stage 2, six sellers make the following decisions on qualities, prices and whether to apply for quality testing.
According to the quality testing algorithm, which seller(s)' true qualities will be revealed to buyers in Stage 3?

	True quality	Price	Apply for quality testing?	Reported quality
Seller A	2	1.00	Apply	2
Seller B	1	2.00	Apply	1
Seller C	2	3.00	Apply	2
Seller D	3	4.00	Not Apply	
Seller E	2	5.00	Apply	3
Seller F	3	5.00	Apply	3

Your answer to the previous question is correct. Now let's continue to answer the following question.

Question 2.2: From Question 2.1, we know that Sellers A, E and F's products will be selected into the **candidate pool**. For each seller, please decide whether he/she will be turned the **application deposit.**

*Hint: **Application deposit** will be returned to an **applying** seller if his/her product is selected into the **candidate pool**.*

Seller ID	True quality	Price	Apply for quality testing?	Reported quality	Selected into candidate pool?	Seller is returned the application deposit?
Seller A	2	1.00	Apply	2	Yes	○ Yes ○ No
Seller B	1	2.00	Apply	1	No	○ Yes ○ No
Seller C	2	3.00	Apply	2	No	○ Yes ○ No
Seller D	3	4.00	Not Apply			
Seller E	2	5.00	Apply	3	Yes	○ Yes ○ No
Seller F	3	5.00	Apply	3	Yes	○ Yes ○ No

You can use the summary of quality testing algorithm below to help you answer this question:

- **Algorithm Step 1**: Among all applying products, the **quality testing organization** selects products which meet ALL of the following 3 criteria into a **candidate pool**:
  - **(Criterion 1):** Its **reported quality** should be 2 or 3.
  - **(Criterion 2):** Its **price** should the lowest among all applying products with the same **reported quality.**
  - **(Criterion 3):** If its **reported quality** is 2, its **price** should be lower than the lowest **price** among all applying products with **reported quality** 3. If its **reported quality** is 3, then **Criterion 3** is always satisfied.

  The **quality testing organization** returns the **application deposit** (0.1 ECUs) to all applying sellers whose products are selected into the **candidate pool**, if any. The **application deposits** will NOT be returned to applying sellers whose products are NOT selected into the **candidate pool**.

Submit

Figure 3.B.18. Experimental Instructions Screens 35-36

SellersMayApply

Comprehension Question 2.3

Suppose in a certain round, at the end of Stage 2, six sellers make the following decisions on qualities, prices and whether to apply for quality testing.
According to the quality testing algorithm, which seller(s)' true qualities will be revealed to buyers in Stage 3?

	True quality	Price	Apply for quality testing?	Reported quality
Seller A	2	1.00	Apply	2
Seller B	1	2.00	Apply	1
Seller C	2	3.00	Apply	2
Seller D	3	4.00	Not Apply	
Seller E	2	5.00	Apply	3
Seller F	3	5.00	Apply	3

You can use the summary of quality testing algorithm below to help you answer this question:

Your answer to the previous question is correct. Now let's continue to answer the following question.

Question 2.3: After **Algorithm Step 1**, Sellers A, E and F's products are selected into the **candidate pool**.

According to **Algorithm Step 2**, which seller(s)' product(s) will be selected into the **final testing pool**?

- Sellers A and E's products
- Sellers A and F's products
- Sellers E and F's products
- Seller A's product must be selected. Each of Sellers E and F's products has a 50% chance to be selected.
- Seller F's product must be selected. Each of Sellers A and E's products has a 50% chance to be selected.
- None of the sellers

- Algorithm Step 2:
  - **(Algorithm Step 2.1):** If more than one product with **reported quality** 2 are in the **candidate pool** (these products should have the same **price**), randomly select one of them into the **final testing pool**. If there is only one product with **reported quality** 2 in the **candidate pool**, select it into the **final testing pool**. If there is no product with **reported quality** 2 in the **candidate pool**, then skip **Algorithm Step 2.1**.
  - **(Algorithm Step 2.2):** If more than one product with **reported quality** 3 are in the **candidate pool** (these products should have the same **price**), randomly select one of them into the **final testing pool**. If there is only one product with **reported quality** 3 in the **candidate pool**, select it into the **final testing pool**. If there is no product with **reported quality** 3 in the **candidate pool**, then skip **Algorithm Step 2.2**.

Submit

SellersMayApply

Comprehension Question 2.4

Suppose in a certain round, at the end of Stage 2, six sellers make the following decisions on qualities, prices and whether to apply for quality testing.
According to the quality testing algorithm, which seller(s)' true qualities will be revealed to buyers in Stage 3?

	True quality	Price	Apply for quality testing?	Reported quality
Seller A	2	2.00	Apply	2
Seller B	1	3.00	Apply	1
Seller C	2	4.00	Apply	2
Seller D	3	5.00	Not Apply	
Seller E	2	6.00	Apply	3
Seller F	3	6.00	Apply	3

Your answer to the previous question is correct. Now let's continue to answer the following question.

Suppose after **Algorithm Step 2**, Sellers A's product is selected into the **final testing pool** and Seller F's product is randomly selected into the **final testing pool**.

Question 2.4a: Which seller(s)' true qualities will be revealed to buyers in Stage 3?

*Hint: You need to compare the **true quality** with the **reported quality** of Sellers A and F's products.*

- Seller A's product only.
- Seller F's product only.
- Both Seller A and Seller F's products.
- Neither Seller A's product nor Seller F's product.

Question 2.4b Is there any seller(s) who need(s) to pay a lying fee for reporting a false quality? If so, which seller (s) need to pay?

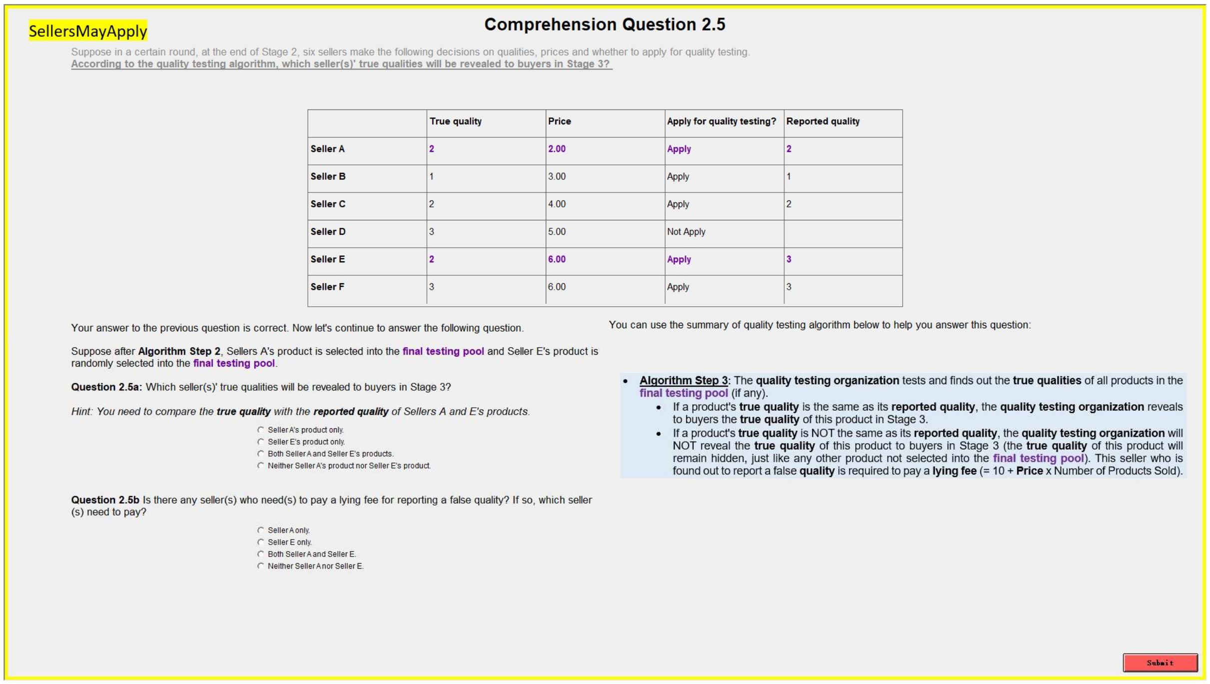
- Seller A only.
- Seller F only.
- Both Seller A and Seller F.
- Neither Seller A nor Seller F.

You can use the summary of quality testing algorithm below to help you answer this question:

- Algorithm Step 3: The **quality testing organization** tests and finds out the **true qualities** of all products in the **final testing pool** (if any).
  - If a product's **true quality** is the same as its **reported quality**, the **quality testing organization** reveals to buyers the **true quality** of this product in Stage 3.
  - If a product's **true quality** is NOT the same as its **reported quality**, the **quality testing organization** will NOT reveal the **true quality** of this product to buyers in Stage 3 (the **true quality** of this product will remain hidden, just like any other product not selected into the **final testing pool**). This seller who is found out to report a false **quality** is required to pay a **lying fee** (= 10 + **Price** x Number of Products Sold).

Submit

Figure 3.B.19. Experimental Instructions Screens 37-38



SellersMayApply

Comprehension Question 2.5

Suppose in a certain round, at the end of Stage 2, six sellers make the following decisions on qualities, prices and whether to apply for quality testing.
According to the quality testing algorithm, which seller(s)' true qualities will be revealed to buyers in Stage 3?

	True quality	Price	Apply for quality testing?	Reported quality
Seller A	2	2.00	Apply	2
Seller B	1	3.00	Apply	1
Seller C	2	4.00	Apply	2
Seller D	3	5.00	Not Apply	
Seller E	2	6.00	Apply	3
Seller F	3	6.00	Apply	3

Your answer to the previous question is correct. Now let's continue to answer the following question.

Suppose after **Algorithm Step 2**, Sellers A's product is selected into the **final testing pool** and Seller E's product is randomly selected into the **final testing pool**.

Question 2.5a: Which seller(s)' true qualities will be revealed to buyers in Stage 3?

*Hint: You need to compare the **true quality** with the **reported quality** of Sellers A and E's products.*

- Seller A's product only.
- Seller E's product only.
- Both Seller A and Seller E's products.
- Neither Seller A's product nor Seller E's product.

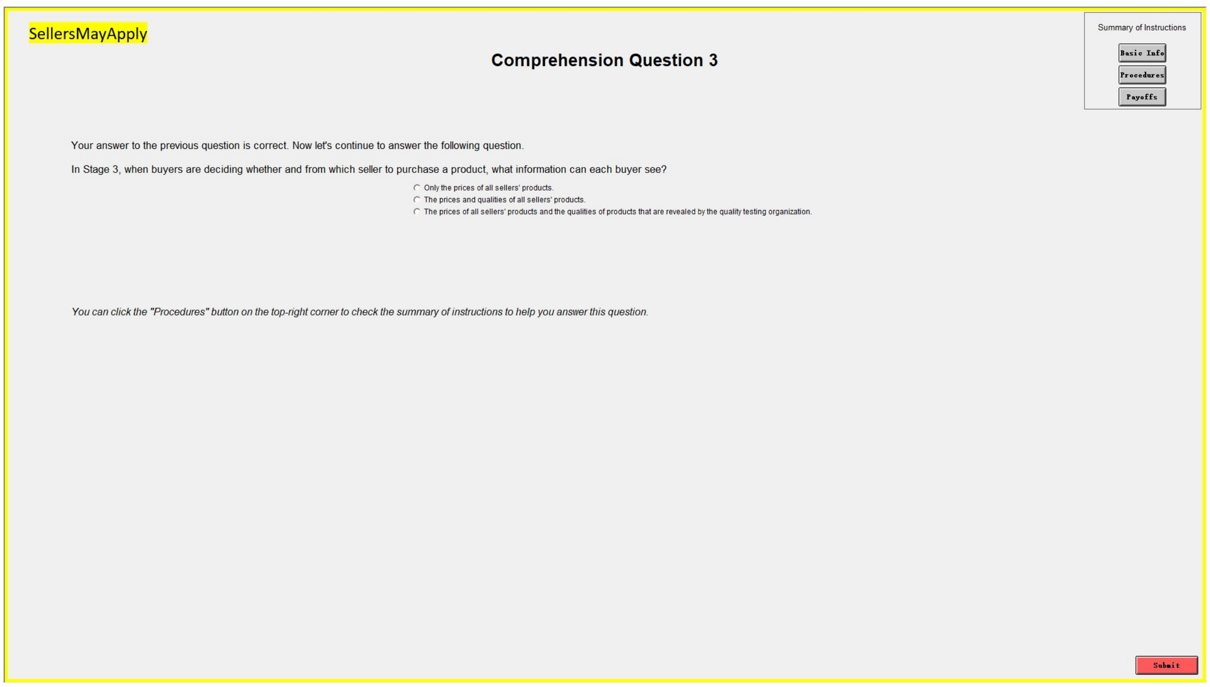
Question 2.5b Is there any seller(s) who need(s) to pay a lying fee for reporting a false quality? If so, which seller (s) need to pay?

- Seller A only.
- Seller E only.
- Both Seller A and Seller E.
- Neither Seller A nor Seller E.

You can use the summary of quality testing algorithm below to help you answer this question:

- **Algorithm Step 3**: The **quality testing organization** tests and finds out the **true qualities** of all products in the **final testing pool** (if any).
  - If a product's **true quality** is the same as its **reported quality**, the **quality testing organization** reveals to buyers the **true quality** of this product in Stage 3.
  - If a product's **true quality** is NOT the same as its **reported quality**, the **quality testing organization** will NOT reveal the **true quality** of this product to buyers in Stage 3 (the **true quality** of this product will remain hidden, just like any other product not selected into the **final testing pool**). This seller who is found out to report a false **quality** is required to pay a **lying fee** (= 10 + **Price** x Number of Products Sold).

Submit



SellersMayApply

Summary of Instructions

Basic Info

Procedures

Payoffs

Comprehension Question 3

Your answer to the previous question is correct. Now let's continue to answer the following question.

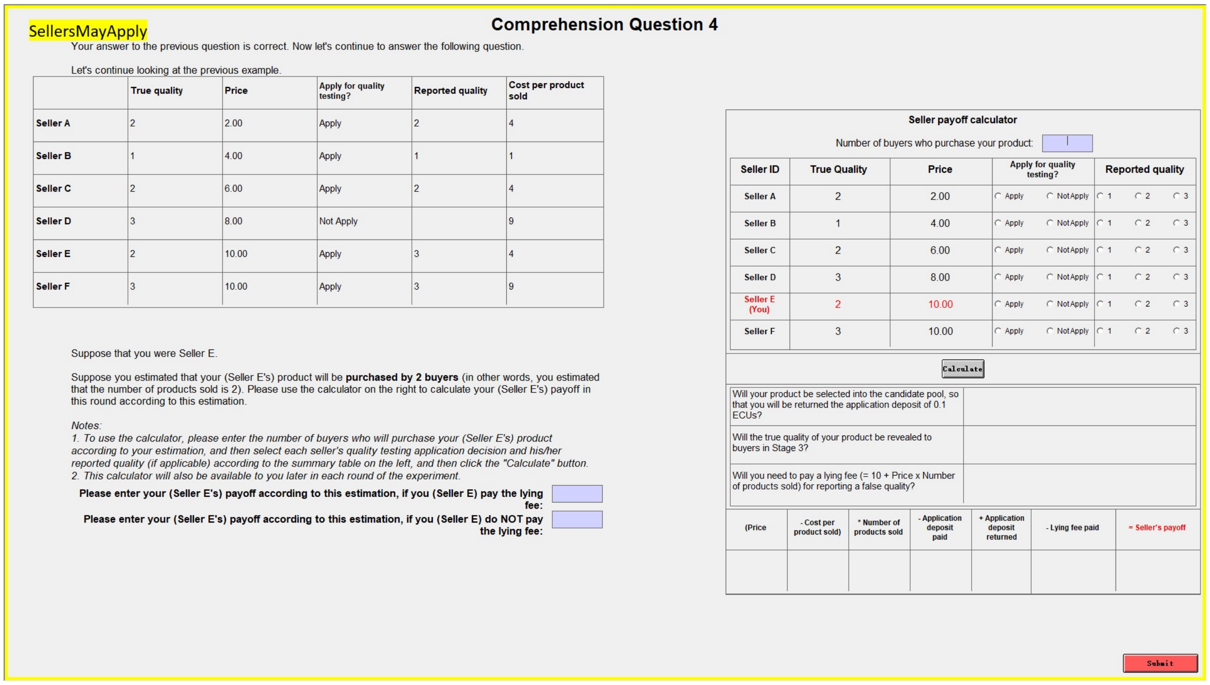
In Stage 3, when buyers are deciding whether and from which seller to purchase a product, what information can each buyer see?

- Only the prices of all sellers' products.
- The prices and qualities of all sellers' products.
- The prices of all sellers' products and the qualities of products that are revealed by the quality testing organization.

You can click the "Procedures" button on the top-right corner to check the summary of instructions to help you answer this question.

Submit

Figure 3.B.20. Experimental Instructions Screens 39-40



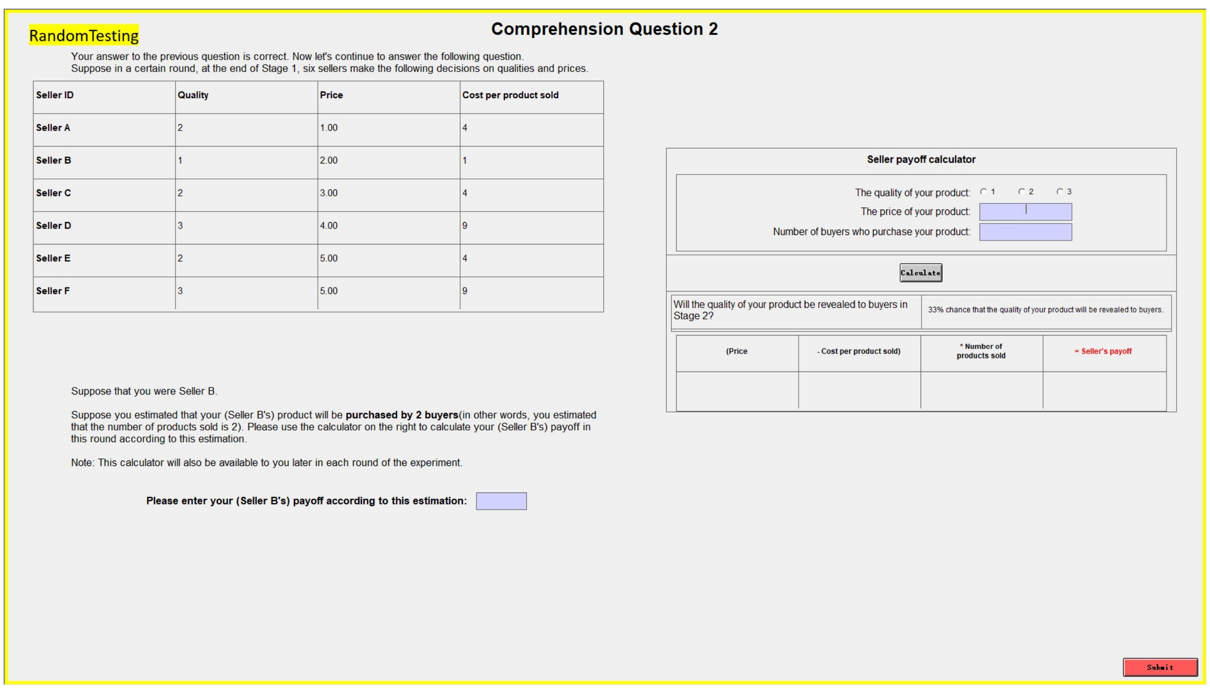
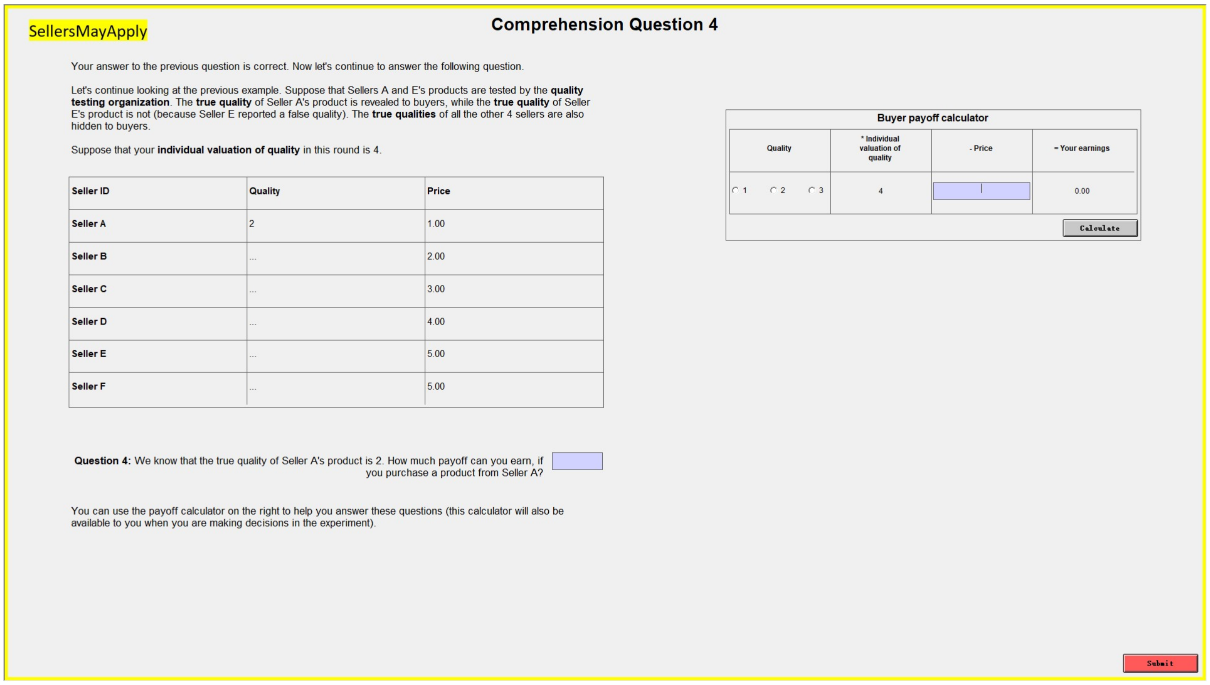


Figure 3.B.21. Experimental Instructions Screens 41-42



SellersMayApply

Comprehension Question 4

Your answer to the previous question is correct. Now let's continue to answer the following question.

Let's continue looking at the previous example. Suppose that Sellers A and E's products are tested by the **quality testing organization**. The **true quality** of Seller A's product is revealed to buyers, while the **true quality** of Seller E's product is not (because Seller E reported a false quality). The **true qualities** of all the other 4 sellers are also hidden to buyers.

Suppose that your **individual valuation of quality** in this round is 4.

Seller ID	Quality	Price
Seller A	2	1.00
Seller B	...	2.00
Seller C	...	3.00
Seller D	...	4.00
Seller E	...	5.00
Seller F	...	5.00

Buyer payoff calculator

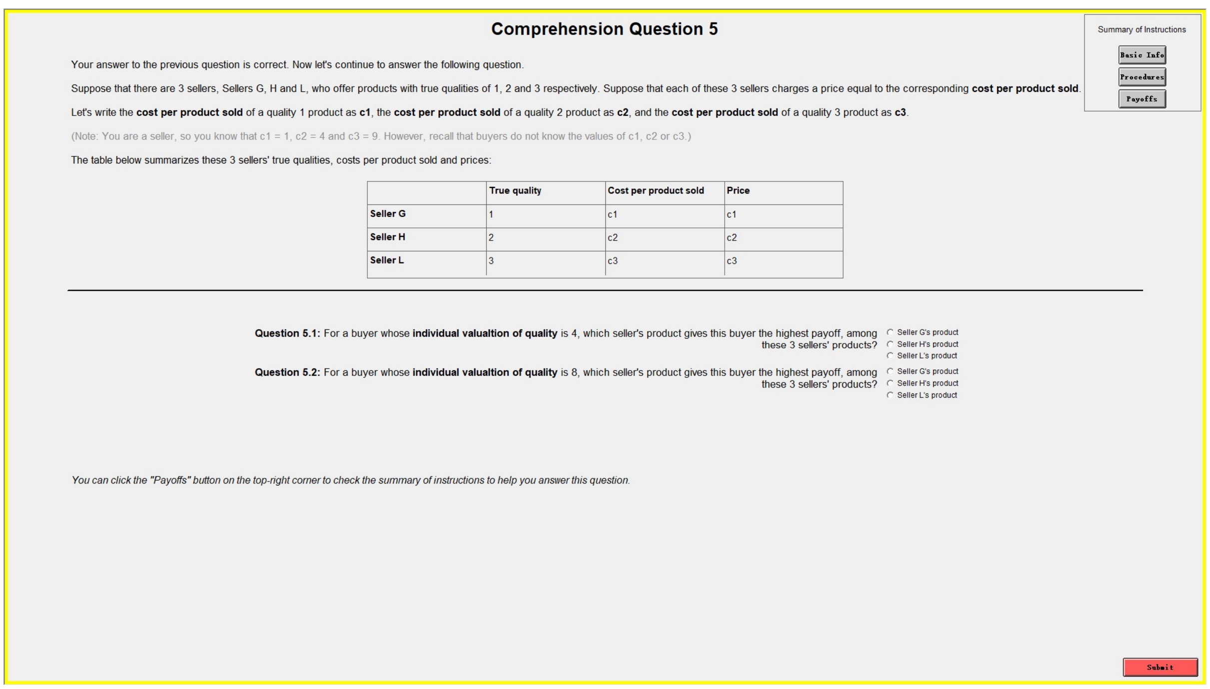
Quality	* Individual valuation of quality	- Price	= Your earnings
1 2 3	4		0.00

Calculate

Question 4: We know that the true quality of Seller A's product is 2. How much payoff can you earn, if you purchase a product from Seller A?

You can use the payoff calculator on the right to help you answer these questions (this calculator will also be available to you when you are making decisions in the experiment).

Submit



Comprehension Question 5

Summary of Instructions

Basic Info

Procedures

Payoffs

Your answer to the previous question is correct. Now let's continue to answer the following question.

Suppose that there are 3 sellers, Sellers G, H and L, who offer products with true qualities of 1, 2 and 3 respectively. Suppose that each of these 3 sellers charges a price equal to the corresponding **cost per product sold**.

Let's write the **cost per product sold** of a quality 1 product as **c1**, the **cost per product sold** of a quality 2 product as **c2**, and the **cost per product sold** of a quality 3 product as **c3**.

(Note: You are a seller, so you know that c1 = 1, c2 = 4 and c3 = 9. However, recall that buyers do not know the values of c1, c2 or c3.)

The table below summarizes these 3 sellers' true qualities, costs per product sold and prices:

	True quality	Cost per product sold	Price
Seller G	1	c1	c1
Seller H	2	c2	c2
Seller L	3	c3	c3

Question 5.1: For a buyer whose **individual valualtion of quality** is 4, which seller's product gives this buyer the highest payoff, among these 3 sellers' products?

- Seller G's product
- Seller H's product
- Seller L's product

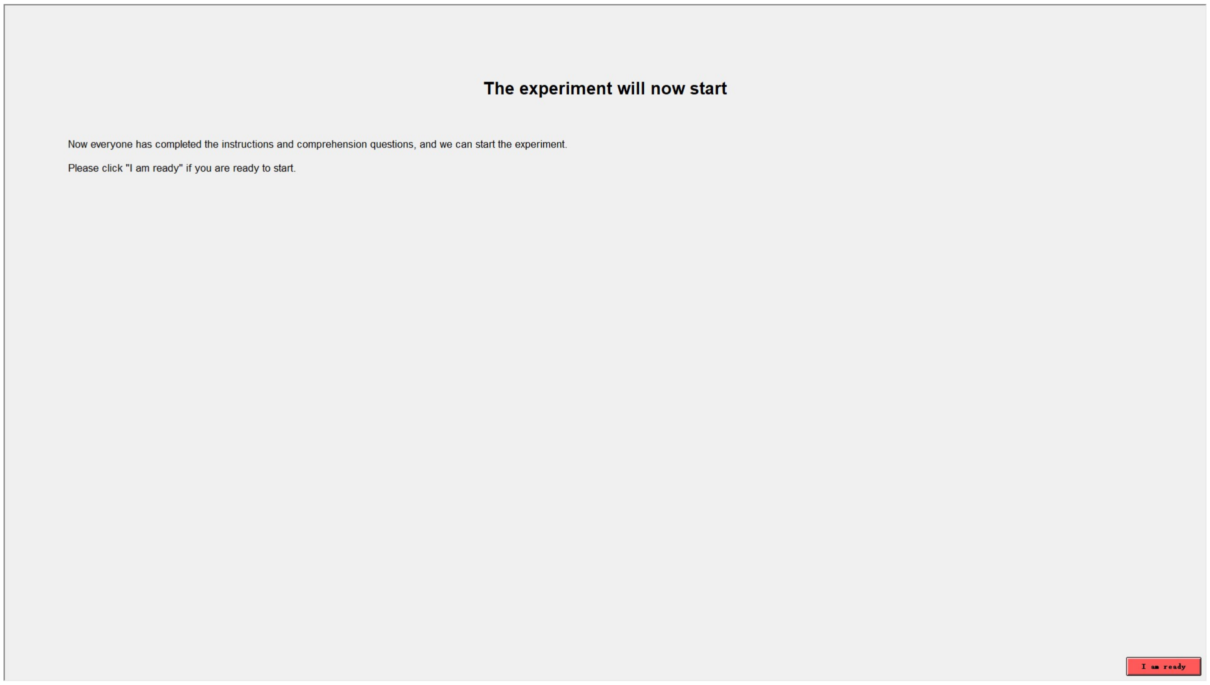
Question 5.2: For a buyer whose **individual valualtion of quality** is 8, which seller's product gives this buyer the highest payoff, among these 3 sellers' products?

- Seller G's product
- Seller H's product
- Seller L's product

You can click the "Payoffs" button on the top-right corner to check the summary of instructions to help you answer this question.

Submit

Figure 3.B.22. Experimental Instructions Screens 43-44



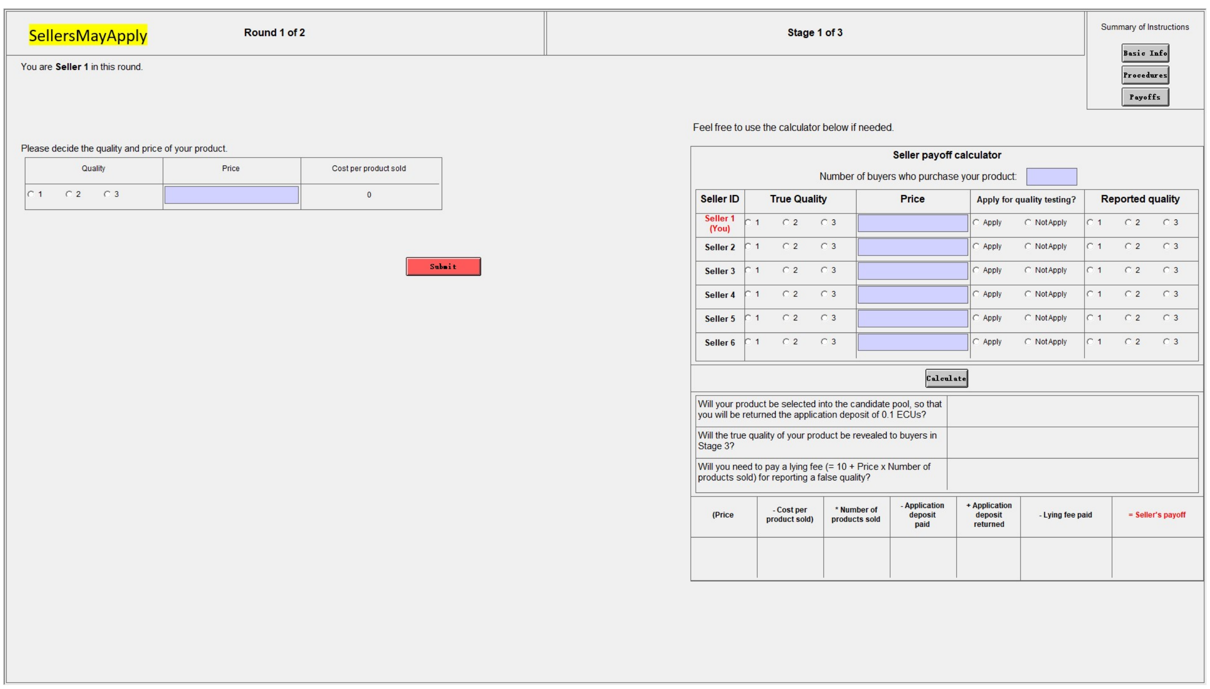


Figure 3.B.23. Experimental Instructions Screens 45-46

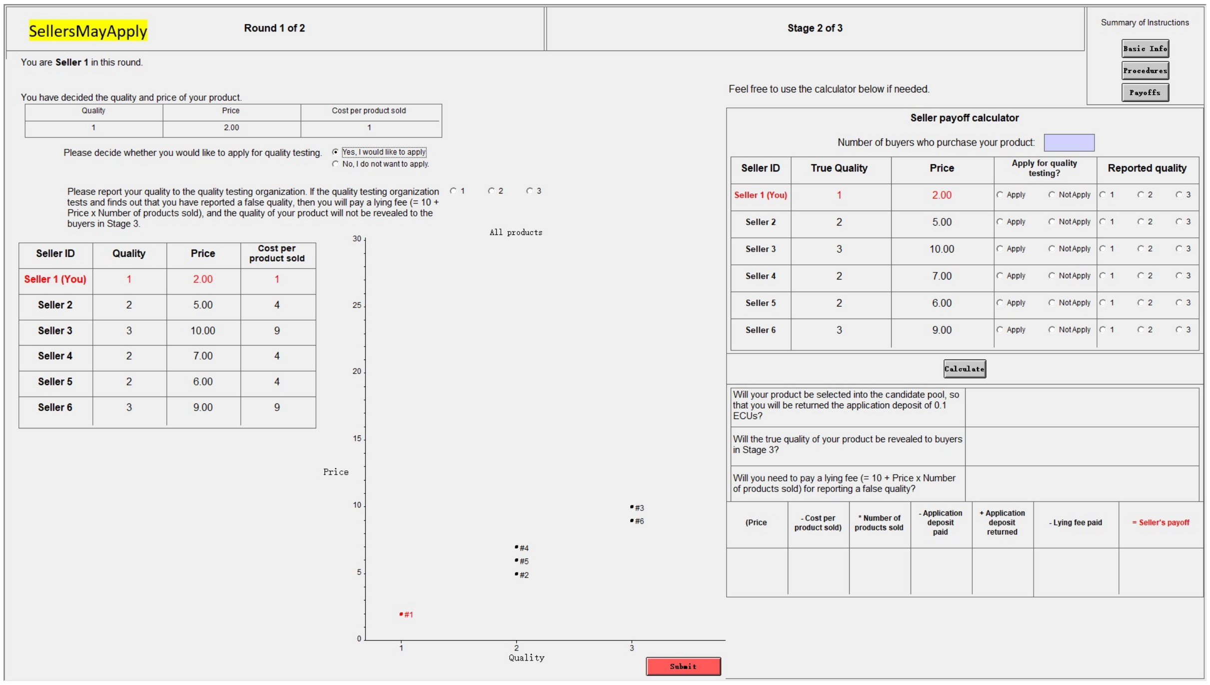
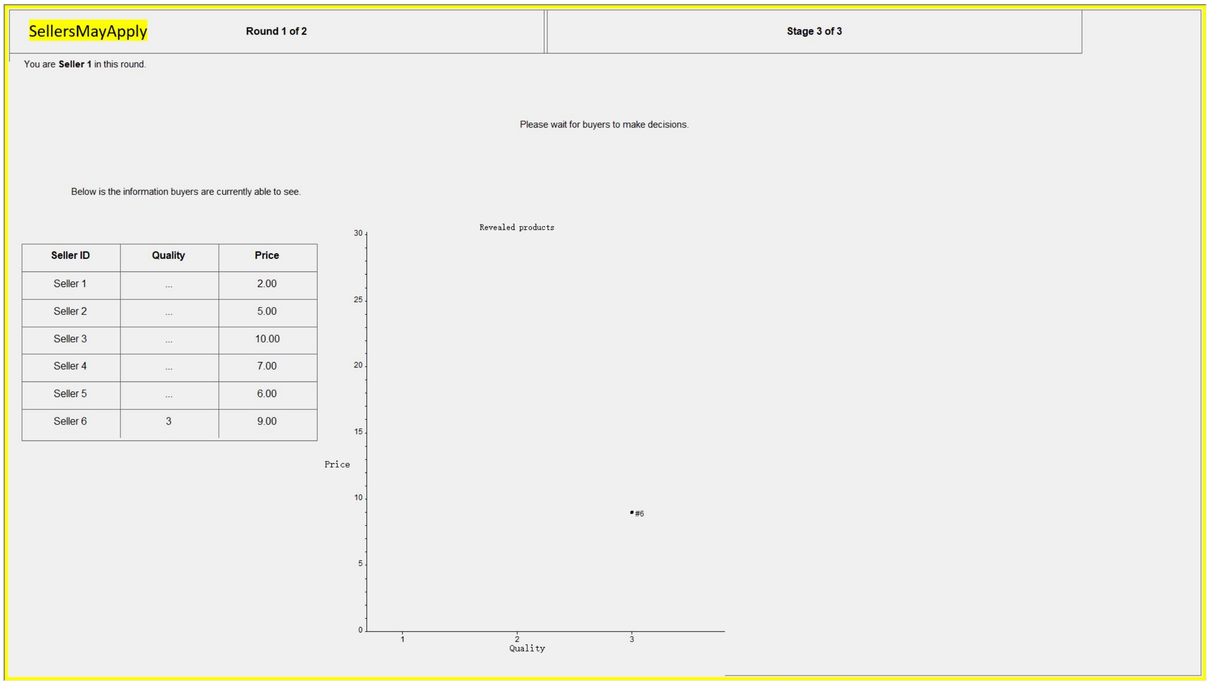


Figure 3.B.24. Experimental Instructions Screens 47-48



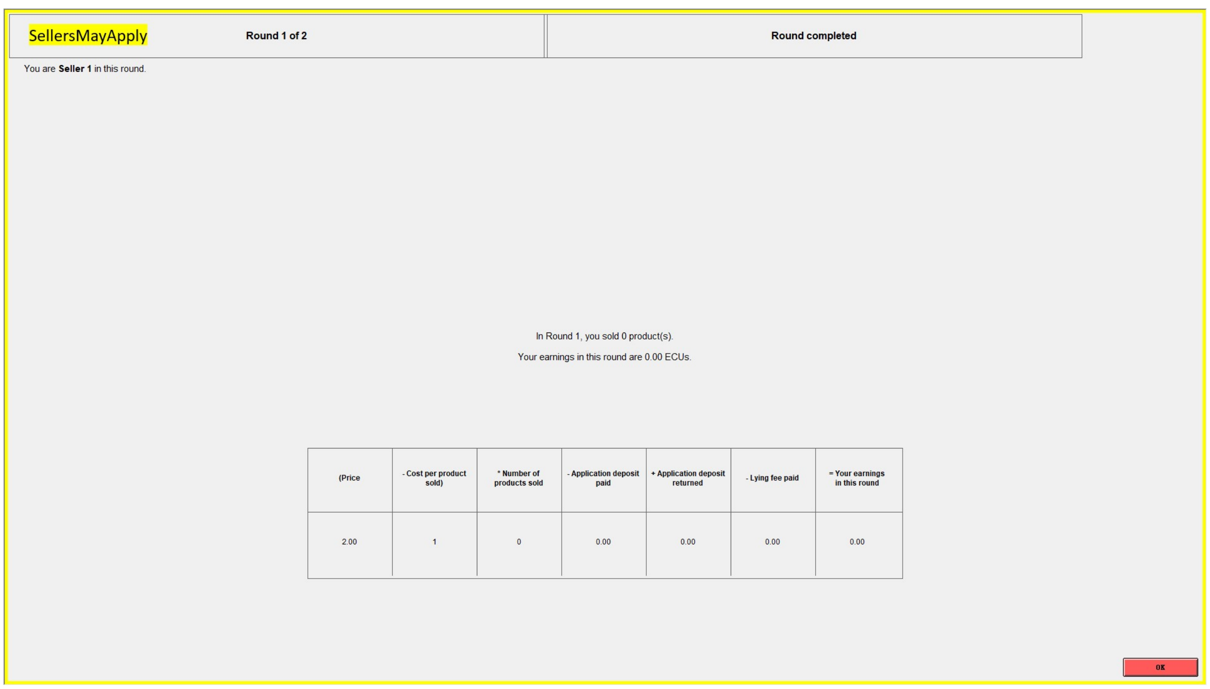
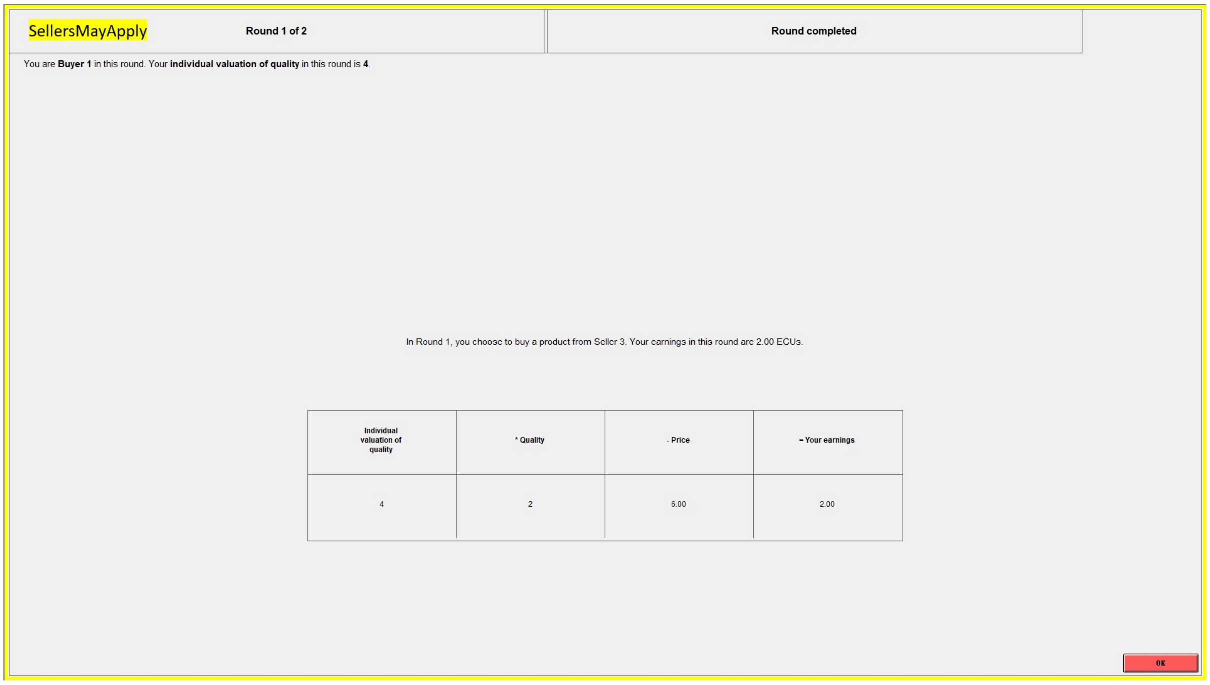


Figure 3.B.25. Experimental Instructions Screens 49-50



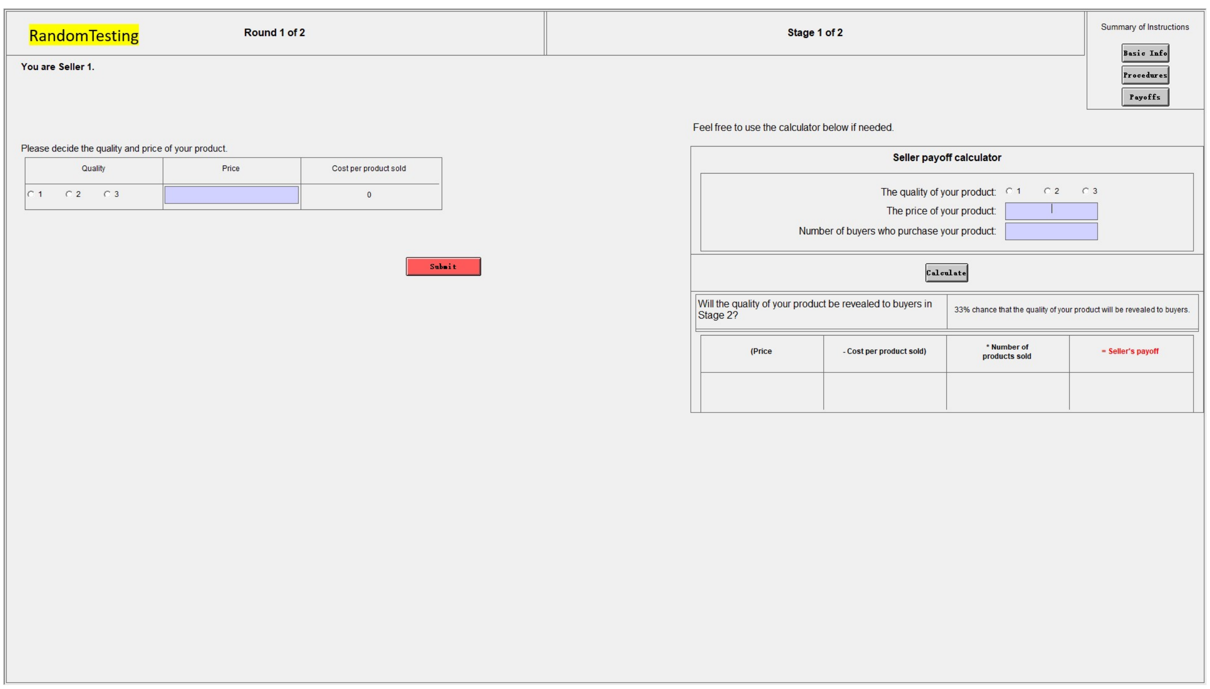


Figure 3.B.26. Experimental Instructions Screens 51-52

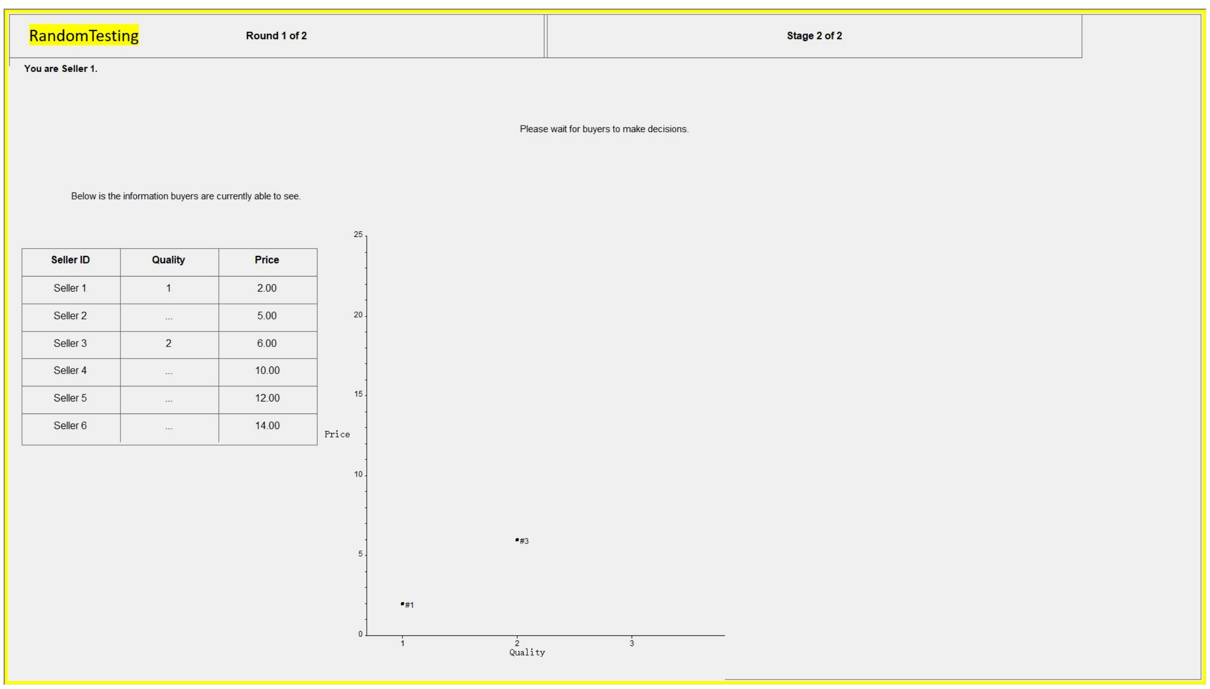
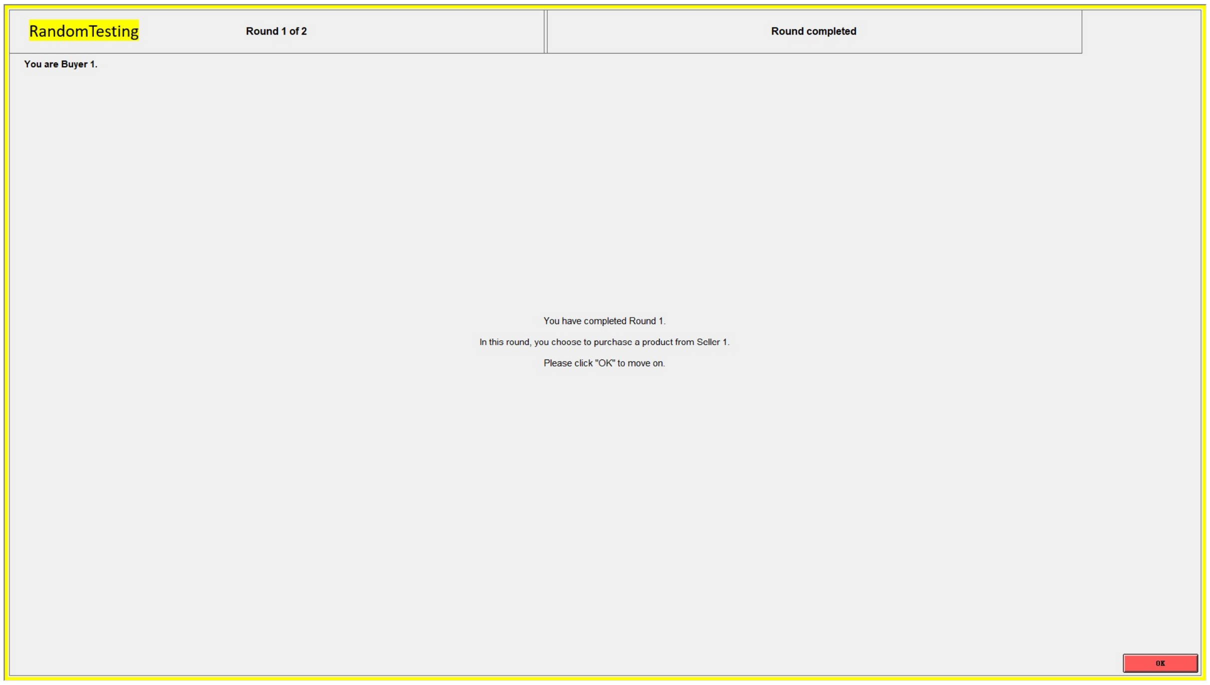


Figure 3.B.27. Experimental Instructions Screens 53-54



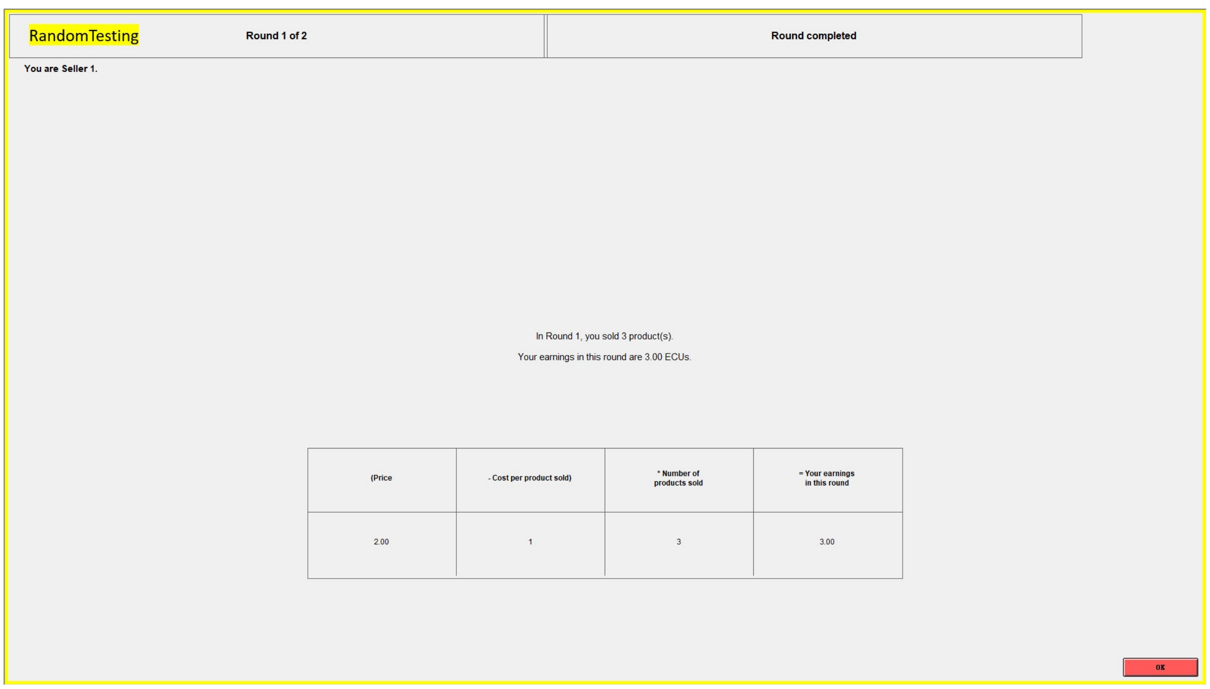


Figure 3.B.28. Experimental Instructions Screens 55-56

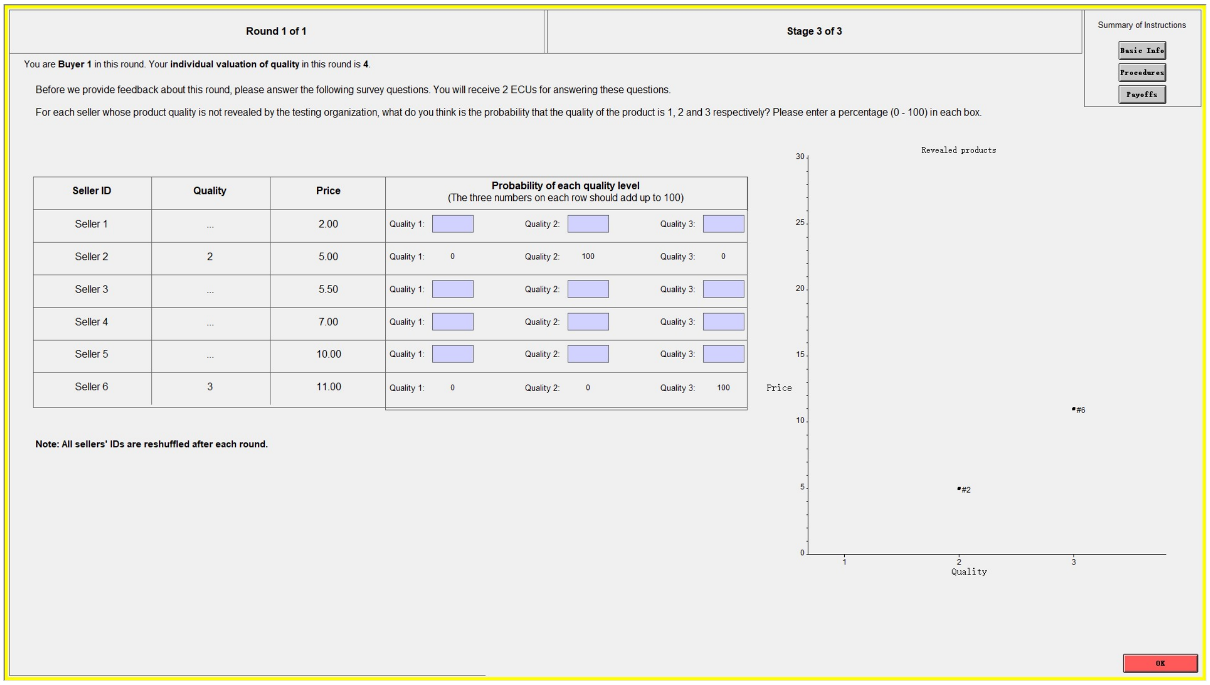


Figure 3.B.29. Experimental Instructions Screen 57

Chapter 4: When Group- and Self-Esteem Lead To "We-Thinking": When Does Social Identity Motivate Group Behavior?

4.1. Introduction

We live, work, and play in social groups. While this membership affords us a number of benefits, it also requires us to make contributions to the group, at times at the expense of individual payoffs. Thus, a question of interest is when and why we choose to contribute to our groups.[55] Social identity, defined as a person's sense of self that is derived from her perceived membership in a social group (Chen & Li, 2009), offers a lens through which to understand the phenomenon of group contribution. In the literature, the question of *why* actors contribute is well understood: they are willing to take actions that benefit the social group because there are direct utility gains from their social identity.[56] In this paper, we take as given that social identity motivates individuals to make group contributions and focus on examining the determinants of *when* it motivates these contributions.

[55] There have been many discussions about the relationship between self-interest and collective interest. One well-known example is Adam Smith's argument that different individuals' self-interests promote the interests of the whole society (1776). Another issue is the "tragedy of commons," with numerous studies offering proposed policy designs to resolve the tension between self-interest and common resources (e.g., Hardin, 1968; Wilson et al., 2013). Finally, some studies acknowledge the primitiveness of collective behavior and argue that it is not a simple summation of different individuals' behaviors (e.g., Searle, 1990; Gold & Sugden, 2007).

[56] According to existing economic theories about social identity, these utility gains are achieved by complying with the prescribed behaviors of the social identity (e.g., Akerlof & Kranton, 2000, 2002, 2005) or enhancing the status of the social group (Shayo, 2009).

Experimental economists have found that when an individual's social identity is made salient through priming (e.g., McLeish & Oxoby, 2011; Chen et al., 2014)[57] and/or when people with the same social identity share a common experience (e.g., Eckel & Grossman, 2005) or interest (e.g., Guth et al. 2008), then this social identity can motivate group-regarding behavior. However, priming is difficult to effect in a natural setting or over the long term, and people sharing the same social identity do not always share common experiences or interests (e.g., in workplaces or schools; cf. Akerlof & Kranton 2002). As such, these mechanisms are difficult to implement outside of the laboratory and would be difficult to engineer in field settings.

However, insight from social psychology suggests that the extent to which a person feels positive about her social identity and idiosyncratic aspects of her identity (hereafter, individual identity) may be good predictors of when social identity is likely to affect behavior. Social Identity Theory (Tajfel & Turner, 1986) and Self-categorization theory (Turner & Oakes, 1986) suggest that a person gains utility from both her social identity and individual identity. How much utility her social identity yields depends on the extent to which she feels positive about her social identity based on her comparison of her social group with other reference groups.[58] In similar fashion, how much utility is obtained from her individual identity depends on the analogous comparisons of feelings to reference individuals.[59] Thus, the relative degree of her positive feelings about her social identity and of her positive feelings about her individual identity may be predictive of her tendency to take group-favoring actions.

These ideas are also captured in R. Akerlof's (2016) model; he formally defines a person's group-esteem (self-esteem) as her positive feelings derived from comparing her own group (herself)

[57] Using priming to increase identity salience is first used in social psychology. See, for example, Reicher and Levine (1994) and Forehand et al. (2002).

[58] Specifically, Tajfel and Turner (1979) write, "...Social identity may be positive or negative according to the evaluations … of those groups that contribute to an individual's social identity. The evaluation of one's own group is determined with reference to specific other groups through social comparisons in terms of value-laden attributes and characteristics. Positively discrepant comparisons between in-group and out-group produce high prestige; negatively discrepant comparisons … result in low prestige." (p. 40)

[59] According to Social Comparison Theory (Festinger, 1954), people usually use others who share some idiosyncratic features with them as reference individuals. However, which group(s) or which individual(s) are used as reference groups or individuals are not the focus of this study.

with reference groups (individuals).[60] Akerlof argues that the *relationship* between these forms of esteem predicts engagement in “we-thinking” (a willingness to treat group goals as one’s own).[61]

In this paper, we investigate the relationship between group-esteem (self-esteem) and engagement in “we-thinking”. We first adapt Akerlof’s model (2016) by articulating how group-esteem and self-esteem affect an individual’s willingness to contribute to her group’s payoffs, and we predict that group-esteem (self-esteem) is positively (negatively) correlated with engagement in “we-thinking” behavior. To test these predictions, we conduct a laboratory experiment. In this experiment, we manipulate people’s group-esteem and self-esteem by asking subjects to participate in inter-group and inter-personal competitions which vary the extent to which they feel positive about their social identity and individual identity.

To experimentally proxy for group-esteem and self-esteem, we use rank-based measures and self-reported measures. Our rank-based measures use the rank of the performance of one’s group (hereafter, *group rank*) and the rank of one’s individual performance (hereafter, *individual rank*). Our self-reported measures (hereafter, *self-reported group-esteem* and *self-reported self-esteem*) ask subjects to report the extent to which they feel good about their group’s and their individual performance in the competitions.[62] Each subject’s “we-thinking” is measured by the number of tokens she allocates to maximize group payoffs at a cost to her individual payoff.

Our experimental results regarding the relationship between self-reported esteem and “we-thinking” support our theoretical predictions: We find that subjects’ self-reported extent to which they feel good about their group’s (individual) performance is significantly positively (negatively) correlated with the number of tokens they allocate to their group, holding their self-reported extent to which they feel good about their individual (group’s) performance constant. With respect to the

[60] The original phrase Akerlof (2016) uses to describe the positive feeling derived from the group’s relative performance is “esteem one accords her group”. In this paper, it is abbreviated to “group-esteem”.

[61] In social philosophy, Sugden (2000) uses the concept “team reasoning” to describe an individual’s propensity to treat herself as a component of a group and pursue the group’s objective. Different from economic theories, his theory of team reasoning uses the group as one single unit of agency.

[62] We use rank-based measures because it is commonly used in experimental economics and presumably the basis of people’s positive feelings derived from intergroup and inter-personal comparisons; however, the self-reported measures may be closer to the psychological construct articulated in Tajfel and Turner (1979) and Akerlof (2016). The rank-based measures and self-reported measures are presumably both highly correlated with group and self-esteem and thus mutually highly correlated as well. We test whether they perform similarly when we use them to predict “we-thinking” behavior.

relationship between rank-based measures and engagement in "we-thinking", we find that when group rank is high, individual rank is significantly negatively correlated with "we-thinking", but this correlation disappears when group rank is low.

Our findings contribute to the literature on group behavior and social identity. We demonstrate that measurable features of groups and individuals can be used to predict *when* people are willing to contribute to a social group at the expense of their individual benefit. Second, to the best of our knowledge, this is the first study which empirically tests how group-regarding behavior is *jointly* affected by group rank and individual rank, and we show that a person's individual rank can play a crucial role in her willingness to take group-regarding behavior when interacting with group rank.

The rest of the chapter is organized as follows. Section 4.2 reviews relevant literature and Section 4.3 presents the theoretical motivation for this study. Section 4.4 describes the experimental design. Section 4.5 lists the hypotheses in the context of the experiment. Section 4.6 provides our experimental results and analysis. Section 4.7 discusses our interpretations of the results and possible implications. Section 4.8 concludes.

4.2. Literature Review

4.2.1. Why Group-Esteem and Self-Esteem Affect "We-Thinking" According to Insights from Social Psychology and Akerlof's Theory

Tajfel and Turner's Social Identity Theory (1979) suggests that a person's subjective evaluation of her social group, based on her comparison of her group with other reference groups, affects the extent to which she associates herself with the social group. They note that people's identification with social groups are "relational and comparative," and "positively (negatively) discrepant comparisons between in-group and out-group produce high (low) prestige." (p.40) When a social identity is negative or unsatisfactory, which leads to low prestige, she is more likely to associate herself less with (i.e., place less weight on) the social group. From a behavioral perspective, it is reasonable to argue that this psychological dissociation will lead to weaker willingness to engage in behavior that benefits the social group.

Apart from social identity, each person also has an identity as an idiosyncratic individual (i.e., individual identity) (Turner & Oakes, 1986). Self-categorization Theory posits that there is a "functional antagonism" between a person's individual identity and social identity regarding the "degree to which they are functionally pre-potent in determining self-perception in any given situation." (p.241) Said differently, both social and individual identity enter utility and the "functional antagonism" could be expressed as opposing weights on the individual and social identity components of the utility function. Changes in positive or negative discrepant comparisons between self and others, or between one's social group and an outgroup, could cause a shift in the weights. Thus, for example, a negative discrepant comparison between self and others leads a person to lower the relative weight placed on individual identity, and then the social identity is more likely to receive a larger relative weight in the utility function. This should lead to stronger willingness to engage in "we-thinking".

Echoing the insight from Social Identity Theory and Self-categorization Theory, R. Akerlof (2016) points out that people's positive feelings derived from inter-group and inter-personal comparisons can be decisive in shifting weight between the identity of a social group and the identity as an individual. He uses the words *esteem one accords her group* (*group-esteem*) and *self-esteem* to describe an individual's positive feelings stemming from her judgment of the relative performance of her group and herself.

Akerlof argues that a more positive feeling derived from a person's group (individual) relative performance or, using his terminology, a higher group-esteem (self-esteem), should lead to a stronger (weaker) willingness to engage in "we-thinking", holding all other factors constant. In other words, group-esteem (self-esteem) should be positively (negatively) correlated with engagement in "we-thinking," holding self-esteem (group-esteem) constant.

4.2.2. Group Rank and Individual Rank as Proxies for Group-Esteem and Self-Esteem

One possible reason for a lack of empirical evidence that tests Akerlof's theory is that group-esteem and self-esteem are two psychological concepts which are hard to observe. However, Social Identity Theory (1979) suggests that *group rank* and *individual rank*, defined as the relative position of a group or an individual (respectively) based on some commonly agreed external criterion(-a), might be a valid proxy for group-esteem and self-esteem. Tajfel and Turner use the word "status" to describe the relative position of a social group, and they point out that the status of a group "reflects a group's relative position on some evaluative dimensions of comparison." (p.19) Therefore, it can be argued that when the "evaluative dimensions of comparison" is unique or commonly agreed upon, rank should be highly correlated with the extent to which people feel positive about their group.[63]

As a variable whose criteria are externally and socially determined, group rank and individual rank are easier to manipulate and observe and thus have been used by some economists to predict behavior.[64] However, little has been done to investigate group-regarding behavior when *both* group rank and individual rank are taken into consideration. Economists have empirically investigated how group rank affects group-regarding behavior. There has been empirical evidence which demonstrates that members of high-ranking groups are more likely to take actions that either enhance the group's welfare or are the preferred actions of other group members. In one study, Charness et al. (2007) show that people with implicitly high group ranks tend to behave more aggressively in both the prisoner's dilemma and battle of sexes games in the hopes of earning more for their groupmates. In another study, Tsutsui and Zizzo (2014) show that high-ranking group

[63] For example, the rank of a soccer club in its national league is one of the evaluative dimensions of comparison that is commonly agreed upon, so it should be highly correlated with the extent to which people feel positive about the club.

[64] In political economics, Moldovanu et al. (2007) design an optimal hierarchy system to maximize contestants' output.

members discriminate more than do low-status group members in deciding on how much to give between group members and outgroup individuals.[65]

Few studies in economics investigate how individual rank affects group-regarding behavior. Studies exploring the role of individual rank mainly focus on how it affects behavior *among different individuals*. These studies find that high-ranking individuals use their high ranks to their own advantage. Specifically, Hoffman et al. (1994) show that subjects tend to offer less money in an ultimatum game when they have earned the right to become first movers by performing well on an exam. This first-mover behavior in the treatment sessions may stem from a feeling that they have a higher rank than their counterparts. More recently, several laboratory experiments directly manipulate individual rank (e.g., "the winner" or highest score). Using this type of rank assignment, Ball et al. (2001) show that higher-ranking participants earn more in a market setting. Ball and Eckel (1996, 1998) find that subjects offer more to higher-ranking counterparts in the ultimatum game, and Oxoby and Spraggon (2008) as well as Duffy and Kornienko (2005) show that a higher rank leads to more selfish choices in dictator games.[66]

In the next section, we extend Akerlof's theory by articulating how group-esteem and self-esteem affect the weights an individual puts on her social identity and individual identity in her utility function, which in turn determine the extent to which she is willing to engage in "we-thinking".

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[65] A number of other papers focus on how rank or status affects individual behavior. These studies find that people with high group rank are more likely to comply with social norms (Tanaka & Camerer, 2016; Butler, 2014; Bauer, 2020). There is also experimental evidence showing that people with a recent increase in status are less likely to trust both ingroup and outgroup members (Suchon & Villeval, 2019). Bhattacharya and Dugar (2014) find that people are more likely to collaborate with others who share the same social status.

[66] Hong and Bohnet (2007) assign individual ranks based on subjects' relative performance in a calculation task, and they demonstrate that high-ranking individuals are more averse to being betrayed when they trust others. Additional literature examines the impact of ranks or status obtained or conferred outside the laboratory setting. For example, Kumru and Vesterlund (2010) find that overall donations are higher when potential donors first see high-status individuals donating. This suggests that low-status individuals tend to follow high-status individuals' donation behavior. There is also empirical evidence showing that feeling or being in high social ranks or status can impact performance. For example, Hoff and Pandey (2014) find that a low-caste Indian subject tends to perform worse on a given task when her caste is revealed to other subjects prior to the task. Bendersky and Shah (2012) find that employees whose rank is elevated during the course of their study perform worse than those who maintain high ranks throughout and no better than those who maintain low ranks. See also Koster and Aven (2018) who investigate how the individual rank and team performance of NBA players affects the number of teammates the players follow on Twitter. They find that high-ranking players (i.e., All-star players) on low-performance teams follow fewer teammates on Twitter than do their counterparts on high-performance teams.

4.3. Theoretical Motivation

"We-thinking" is defined as "a mode of thinking in which an individual takes a group's goal as his own (Akerlof, 2016, p.415)." In Akerlof's we-thinking theory, an important premise is that self-esteem and group-esteem are first-order motives for behavior.[67] One important prediction of this theory is that, given a set level of self-esteem (group-esteem), people with higher group-esteem (self-esteem) are more (less) likely to engage in "we-thinking."

To map this model into an experimental setting, we characterize an actor's decision-making behavior as facing a tradeoff between allocating resources to herself and allocating resources to her group. We begin by assuming that the individual has a preferred action that she would take absent any group considerations (i.e., if group information is not salient at the time of the decision). We further assume that there is an action that complies with the group norm.[68] We take x_i as a parameter that denotes the personally-preferred action and x_g^N as a parameter that denotes the action consistent with the group norm.

In our formalization of the model, actors are heterogeneous with respect to the value they place on actions that deviate from the group norm. We write an individual's utility function in the form of a weighted average:[69]

$$U = \frac{w(E_i)[-(x - x_i)^2] + w(E_g)[-\left(x - x_g^N\right)^2]}{w(E_i) + w\left(E_g\right)}. \tag{90}$$

In the above specification, an individual's chosen allocation to her group, x, represents the tradeoff between x_i and x_g^N. We assume that $x_i < x_g^N$ because allocating more resources to the group usually comes at the expense of individual benefits. $w(.)$ is the weight the individual places on adhering to x_i or x_g^N and is positively correlated with E_i or E_g (i.e., $w' > 0$). The negative quadratic form of (90) requires the individual to choose an x that balances the (weighted) distance

[67] This premise is taken from the theory as developed by Tajfel and Turner (1979). In our study, we treat self-esteem and group-esteem as exogenous to a particular situation. They can be treated endogenously in a more general model, but this is not our focus here.

[68] This assumption and its intuition closely follow that in Benjamin et al.'s work (2010). Performance here refers to any measurable and observable (to others) attribute that can be ranked.

[69] This utility function is adapted from Benjamin et al.'s model (2010).

between x and x_i and the (weighted) distance between x and x_g^N.[70] The first-order condition of the utility function identifies the individual's optimal action:

$$x^* = \frac{w(E_i)x_i + w\left(E_g\right)x_g^N}{w(E_i) + w\left(E_g\right)} \tag{91}$$

The central mechanism of "we-thinking" is that the weights are determined by an individual's level of self-esteem or group-esteem, which she perceives based on a comparison between her own / group's performance and the performance of other reference individuals / groups.[71] Formally, a person i's group-esteem E_g is:

$$E_g = N(g) - \frac{1}{|F_G|}\sum_{g' \in F_G} N(g'), \tag{92}$$

where $N(g)$ denotes her absolute judgment of her group's performance and F_G denotes the set of all reference groups. This functional form suggests that her group-esteem reflects how positively she perceives her group performs compared with the average performance of all reference groups. Analogously, a person's self-esteem, E_i, is derived from a comparison between her own performance and that of other reference individuals:

$$E_i = N(i) - \frac{1}{|F_I|}\sum_{k \in F_I} N(k), \tag{93}$$

where $N(i)$ denotes her absolute judgment of her own performance and F_I denotes the set of all reference individuals. Her self-esteem reflects how positively she thinks of her own performance compared with the average performance of all reference individuals.[72]

Using the above specification, a change in E_i (E_g) alters the extent to which the individual is willing to choose the group norm compliant action (x_g^N). Taking the derivatives of x^* with respect to E_g and E_i from (91), we have:

$$\frac{\partial x^*}{\partial E_g} = \frac{w(E_i)\left(x_g^N - x_i\right)w'\left(E_g\right)}{\left(w(E_i) + w\left(E_g\right)\right)^2} > 0 \tag{94}$$

[70] This captures the functional antagonism referenced by Self-categorization Theory (Turner & Oakes, 1986).
[71] How an individual determines reference groups and individuals is an interesting question but is not our focus in this paper.
[72] The expressions of E_g and E_i in (92) and (93) are adapted from Akerlof's model (2016).

$$\frac{\partial x^*}{\partial E_i} = \frac{w(E_g)(x_i - x_g^N)w'(E_i)}{\left(w(E_i) + w(E_g)\right)^2} < 0. \tag{95}$$

Here, (94) and (95) imply that: a) holding self-esteem (E_i) constant, when E_g increases, x^* will also increase and thus move closer to x_g^N and b) holding group-esteem (E_g) constant, when E_i increases, x^* will decrease and thus move closer to x_i.

4.4. Experimental Design

To test the above predictions, we conduct a laboratory experiment consisting of sessions comprised of six subjects each.[73] We use z-Tree (Fischbacher, 2007) to program this experiment. In each session, subjects have the experimental instructions read aloud to them prior to completing each task.

The experiment consists of four stages. In Stage 1, subjects are assigned to two 3-person groups based on their indicated preferences among a series of paintings. In Stage 2, their group-esteem and self-esteem are manipulated by incentivized interpersonal and inter-group competitions. In Stage 3, they are asked to allocate a set number of tokens between their personal account and their group's account. In Stage 4, their feelings of group attachment, self-reported self-esteem, and self-reported group-esteem are measured by their responses to several 7-point Likert survey questions.

The experiment consists of two treatments: *TreatInfo* and *Control*. Subjects in the *TreatInfo* treatment receive information about their group ranks and individual ranks before being asked to allocate tokens between their personal and group's accounts. Subjects in the *Control* treatment do not receive any performance information prior to completing their allocations. Both treatments consist of the above four stages.

[73] Note that there were 12 subjects physically present in the laboratory at the same time for some of the sessions. However, these 12 subjects were randomly assigned to two independent 6-person sessions that did not change throughout the experiment. Furthermore, subjects were clearly informed that they would interact only with 5 other subjects in the same 6-person session.

Subjects receive an $8 show-up fee as well as a final payment based on the task outcome. To mitigate any potential income effect from Stage 2 (the incentivized interpersonal and inter-group competitions) that may affect allocation decisions in Stage 3, the computer randomly determines for each subject whether the outcome in Stage 2 or Stage 3 is used to determine her final payoff at the end of the experiment.

The following subsections describe the experimental procedures in each stage in detail.

4.4.1. Stage 1: Group Assignment

In Stage 1, we assign subjects to different groups based on their indicated preferences for different paintings. The procedure in this stage mainly follows Chen and Li's design (2009) with a few changes to guarantee that the number of subjects in each group is the same.

In the group assignment stage, six subjects are assigned to one of two groups based on their reported preference regarding five pairs of paintings.[74] In each pair, there is one painting by Paul Klee and one painting by Wassily Kandinsky. Each subject independently chooses which painting she prefers in each pair without being told the artist of each painting. After all subjects make their decisions, the computer sorts the six subjects based on how many Klee paintings they prefer (if there are multiple subjects who prefer the same number of Klee paintings, then these subjects' orders are determined randomly). The first three subjects who prefer the most Klee paintings are classified into Group Klee. The other three subjects, who indicate a preference for Klee paintings less often, are classified into Group Kandinsky. Subjects in Group Klee are privately told that all of their group members relatively prefer Klee paintings, compared with other subjects. Subjects in Group Kandinsky are privately informed that all of their group members relatively prefer

[74] The five pairs of paintings are: 1a—*Gebirgsbildung* (1924), by Klee; 1b—*Veiled Glow* (1928), by Kandinsky; 2a—*Dreamy Improvisation* (1913), by Kandinsky; 2b—*Warning of the Ships* (1917), by Klee; 3a—*Dry-Cool Garden* (1921), by Klee; 3b—*Landscape with Red Spots* (1913), by Kandinsky; 4a—*Gentle Ascent* (1934), by Kandinsky; 4b—*A Hoffmannesque Tale* (1921), by Klee; 5a—*Development in Brown* (1933), by Kandinsky; 5b—*The Vase* (1938), by Klee.

Kandinsky's paintings.[75] Subjects do not receive information about any other subject's group membership. Groups remain the same for the entire experiment.

4.4.2. Stage 2: Interpersonal and Intergroup Competitions

In Stage 2, subjects in both treatments participate in a two-round competition in which they answer questions from an established IQ test. All the IQ test questions are selected from Raven's Standard Progressive Matrices (SPM Plus) (1998).[76] The first round of the game intends to vary their individual ranks and thus vary their self-esteem, while the second round intends to vary their group ranks and thus vary their group-esteem.

In the first round of the game,[77] all subjects are assigned into pairs in which the two subjects are from different groups (i.e., one subject is from the Klee group and the other is from the Kandinsky group). Each pair participates in a competition in which they are asked to solve as many questions as possible within five minutes. At the end of the first round, the subject who correctly solves more problems within each pair wins the first round of the game and receives a $2.50 bonus, while the subject who loses the first round receives $0. In the remainder of this paper, we call the first round of Stage 2 the "individual battle."

In the second round of the game, each subject is again given five minutes to solve as many questions as possible. At the end of the second round, the computer calculates the total number of correct answers across all members of a three-person group. The group with the greater number of total correct answers wins the second round and each of the three group members receives a $2.50 bonus, while each of the three group members in the group that loses the second round receives $0. In the remainder of this paper, we call the second round of Stage 2 the "group battle."[78]

[75] Sorting subjects according to how many Klee's paintings they prefer and then classifying them into two groups is our deviation from Chen and Li's original design (2009). This is to guarantee that we have the same number of subjects in each group.

[76] The experimental instructions that introduce the Raven's Matrices are adapted from Falk and Szech (2019).

[77] We call the first round "Competition 1" and the second round "Competition 2" in the experimental instructions. This is to avoid possible confusion associated with the terms "Round" and "Stage."

[78] The reason we use two rounds instead of only round to determine the group rank and individual rank separately is to make it more difficult for subjects to use their two ranks to infer other group members' individual ranks, so that it will be more difficult for them to form beliefs about other group members' potential contributions to the group in Stage 3.

After the second round of the game, each subject in the *Control* treatment receives a screen message indicating that Stage 2 is finished. By contrast, each subject in the *TreatInfo* treatment receives the screen message as well as information on whether she has won the individual battle and whether her group have won the group battle. However, she is not told the number of questions she or her group answered correctly nor other subjects' game results.

4.4.3. Stage 3: Modified Dictator Game

In both the *Control* and *TreatInfo* treatments, we elicit subjects' engagement in "we-thinking" in Stage 3. In this stage, we ask each subject to play a modified version of the dictator game in which she decides how to allocate six tokens between her personal account and her group's account. Each token allocated to her personal account is worth \$1.00, while each token allocated to her group's account is worth \$1.50. At the end of this stage, the computer randomly selects one subject in each group to determine the payoffs to the group. If a subject's decision is randomly selected to determine the group's payment, she receives all the money she allocates to her personal account, while the money she allocates to her group's account is evenly shared by the three members of her group, herself included. In other words, this subject's payoff equals \$1.00 * the number of tokens she allocates to her personal account + \$1.50 / 3 * the number of tokens she allocates to her group's account. Each of the two other subjects in her group, whose decisions are not selected for payment, receive a payoff of \$1.50 / 3 * the number of tokens the selected subject allocates to her group's account.

This modified dictator game has the following features. First, in determining the group payoff, the larger the number of tokens the selected subject allocates to the group, the greater the group's total payoff and the lower the payoff difference among the three group members. Thus, a selected subject who allocates all tokens to the group both maximizes the total payoff to the three group members and minimizes the payoff difference among the three group members. This feature of our design ensures that a subject who wants to adhere to the group norm (x_g^N in our model) will always allocate all tokens to the group's account, no matter whether she thinks that the group norm is "efficiency" (i.e., maximizing total payoffs) or "equity" (i.e., minimizing payoff differences).[79] Second, this is a non-strategic game. Compared with strategic games such as public good games, the main advantage of a non-strategic game is that subjects do not need to form beliefs about other group members' contributions when deciding their own group contributions.

4.4.4. Stage 4: Measures for Self-Reported Group-Esteem, Self-Reported Self-Esteem and Group Attachment

In Stage 4, subjects are first asked to answer several 7-point Likert scale questions about the extent to which they feel attached to their groups.[80] Then we elicit their self-reported self-esteem and self-reported group-esteem through Likert scale questions which ask them to report the extent to which they feel good about their individual and group performance in Stage 2 of the experiment,[81] which are adapted from Li et al. (2017).[82, 83]

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[79] Future studies might further investigate *which* norm (i.e., efficiency or equity) group members adhere to, as group-esteem and self-esteem differ. The present study is interested only in *whether* group members are willing to adhere to the group's norm.

[80] These questions are adapted from Aron et al.'s (1992) *Inclusion of the Other in the Self* scale and Li et al. (2017).

[81] Note that each subject is only informed of whether she/her group wins the individual/group battle but not how many questions she/her group or other subjects/group correctly answers, so the individual/group rank is the only available information for esteem formation.

[82] For the sake of the completeness of adapting Li et al.'s Likert scale questions (2017), we also include another set of Likert scale questions which ask subjects to report the extent to which they take pride in their individual and group performance. However, although "pride" is presumably also associated with the extent to which people feel positive about their social/individual identity, we argue that it is less reliable in terms of measuring group-esteem and self-esteem defined in this study (i.e., the extent to which they feel positive about their social/individual identity *based on intergroup and interpersonal comparisons*), due to its ambiguous connotations. As Lea and Webley (1997) point out, pride is sometimes associated with the "seven deadly sins" and considered to be a synonym of narcissism or *groundless* sense of superiority. This connotation implies that the positive feelings derived from this type of pride is not based on one's evaluation of relative performance but on an *exaggerated* and *excessive* basis due to a pathological need for elevation of self-image, which is different from esteem defined in this study.

[83] We put the self-reported esteem elicitation questions after the modified dictator game to avoid an experimenter demand effect on subjects' allocation decisions. Since no subject receives any new information (other than their group ranks and individual ranks) about themselves or any other subject during the modified dictator game stage, the modified dictator game should not impose an information effect on subjects' self-reported esteem. In addition, we do not believe that subjects' self-reported esteem is affected by a self-justification effect from their allocation decisions in Stage 3. We have two pieces of evidence to support this claim. First, the self-reported esteem manipulation check results in Section 4.6.2.1 show that there is a strong and significant correlation between group (individual) rank and self-reported group-esteem (self-esteem). This implies that group (individual) rank should be the main source of self-reported group-esteem (self-esteem). Second, we do not find a significant correlation between the extent to which subjects take pride in their group (individual) performance and the number of tokens allocated to the group (see Table 4.A.2). As we argue in Footnote 24, these pride questions are associated with but not fully consistent with esteem defined in this study. If a self-justification effect were present, then subjects would focus on the association between pride and esteem but ignore the inconsistent part between them to self-justify their allocation decisions when answering the pride questions, and we would find a *significant* correlation between their responses to pride questions and tokens allocated to the group.

4.4.5. Final Payoffs in the Experiment

After subjects in both treatments finish Stage 4, they are shown a final screen which displays all the game results in Stage 2 (i.e., whether they win the individual battle and whether their group wins the group battle), Stage 3 (i.e., whether their decisions are randomly selected and their payoffs), and whether Stage 2 or Stage 3 has been selected to calculate their final payoffs from the experiment.

4.4.6. Summary

A total of 162 subjects participate in the experiment in the School of Information Behavioral Laboratory at the University of Michigan, including 132 subjects in *TreatInfo* and 30 subjects in *Control*.[84] All subjects are students from the University of Michigan. They are recruited via the online recruitment platform ORSEE (Greiner, 2015). Each subject is allowed to participate in only one session. The average payoff of subjects is $10.40, which includes the $8.00 show-up fee. Each session lasts for 40 minutes on average.

4.5. Main Hypotheses

Our discussion in Section 4.3 concludes that a person's engagement in "we-thinking" should be positively (negatively) correlated with group-esteem (self-esteem), holding self-esteem (group-esteem) constant. Since we use group rank (individual rank) and self-reported group-esteem (self-reported self-esteem) as proxies for group-esteem (self-esteem) in the experiment, we should have the following experimental hypotheses.

Holding individual rank constant, we expect that subjects with higher group rank allocate more tokens to their group's account. We further expect that, holding group rank constant, subjects

[84] The sample size was determined as follows: Based on Chen and Chen's (2011) effort difference in the near-minimal treatment, we estimated a 23% difference (1.4 tokens in our experiment) in allocations between subjects with different rank categories, and we estimated a standard deviation of 2 tokens based on our pilot data. With α=0.05 and β=0.80, the required sample size is 32 subjects per rank category on average.

with higher individual ranks allocate fewer tokens to their group's account. In the context of our experiment, each subject's group rank and individual rank are both binary: Subjects who win (lose) the group battle are considered to have a high (low) group rank, and subjects who win (lose) the individual battle are considered to have a high (low) individual rank. Therefore, we expect that subjects with high group rank and low individual rank (hereafter, (Hg, Li) subjects) allocate the largest number of tokens to the group's account, and that subjects with low group rank and high individual rank (hereafter, (Lg, Hi) subjects) allocate the smallest number of tokens to the group's account. Subjects with both high (low) group rank and high (low) individual rank (hereafter, (Hg, Hi) and (Lg, Li) subjects) should allocate fewer tokens than (Hg, Li) subjects do and more tokens than (Lg, Hi) subjects do. Breaking down the relationship between these 4 categories of subjects, we have the following hypotheses:

Hypothesis 1.1: (Hg, Li) subjects allocate more tokens to the group's account than (Hg, Hi) subjects do.
Hypothesis 1.2: (Hg, Li) subjects allocate more tokens to the group's account than (Lg, Li) subjects do.
Hypothesis 1.3: (Lg, Hi) subjects allocate fewer tokens to the group's account than (Hg, Hi) subjects do.
Hypothesis 1.4: (Lg, Hi) subjects allocate fewer tokens to the group's account than (Lg, Li) subjects do.

We also expect that subjects with higher self-reported group-esteem allocate more tokens to the group's account, holding self-reported self-esteem constant, and that subjects with higher self-reported self-esteem allocate fewer tokens to the group's account, holding self-reported group-esteem constant.

Hypothesis 2.1: Subjects with higher self-reported group-esteem allocate more tokens to the group's account, holding self-reported self-esteem constant.

Hypothesis 2.2: Subjects with higher self-reported self-esteem allocate fewer tokens to the group's account, holding self-reported group-esteem constant.

4.6. Results

4.6.1. How Group Rank and Individual Rank Affect "We-Thinking"

We first examine the relationship between group/individual ranks and engagement in "we-thinking".

Figure 4.1 shows the means of tokens allocated to the group for each rank category of *TreatInfo* subjects as well as the results from a set of one-sided t-tests comparing the means between subjects with the same group or individual rank.[85]

[85] Notes: (1) The side of each one-sided t-test is determined by our hypotheses. (2) Only significant results ($p<0.1$) are presented in the figure. (3) The test results are similar if we use a one-sided permutation test: the only significant difference is between *(Hg, Li)* and *(Hg, Hi)* subjects ($p=0.025$).

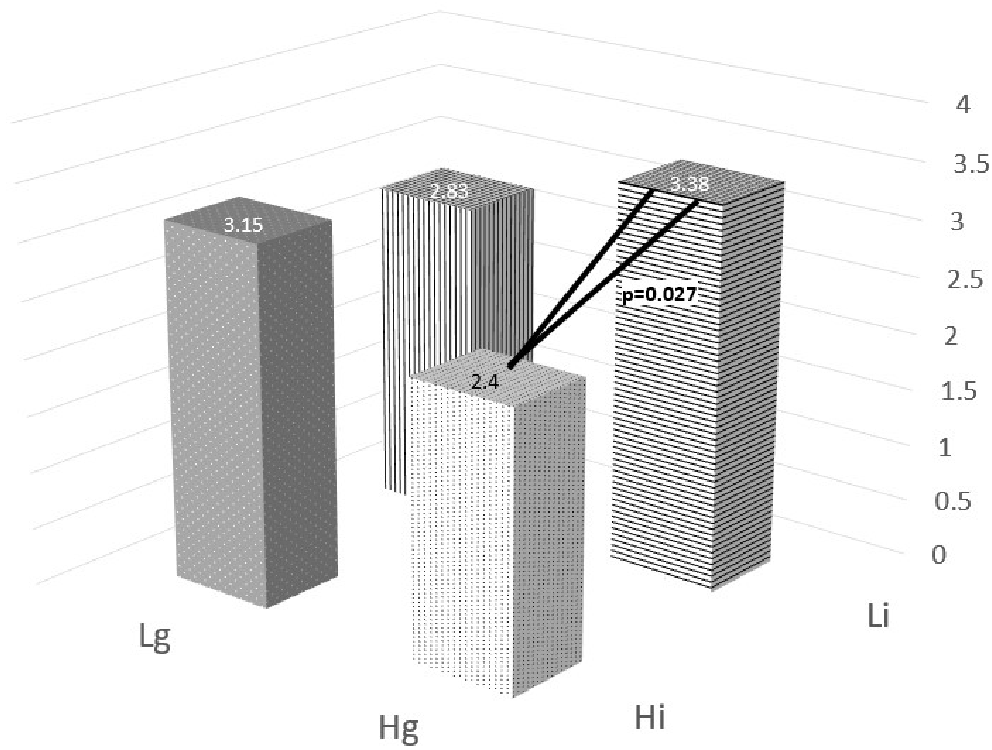

Figure 4.1. Average tokens allocated to the group's account for each rank category (*TreatInfo* subjects only)

From the results in Figure 4.1, we see that (Hg, Li) subjects allocate 3.38 tokens to the group's account on average (56.6% tokens), while (Hg, Hi) subjects allocate 2.40 tokens to the group's account (40% tokens), a difference which is statistically significant (p=0.027). This supports Hypothesis 1.1.

Result 1: (Hg, Li) subjects allocate significantly more tokens to the group's account than (Hg, Hi) subjects do.

We also see that (Hg, Li) subjects on average allocate more tokens to the group's account than do (Lg, Li) subjects, who on average allocate 2.83 tokens (47.2% tokens), but this difference is statistically insignificant. Examining the results further, we see that (Lg, Hi) subjects allocate

3.15 tokens to the group's account on average (52.5% tokens), which is more than the number allocated by (Hg, Hi) subjects and directionally inconsistent with Hypothesis 1.3. On average, (Lg, Hi) subjects allocate more tokens than (Lg, Li) subjects do, which is directionally inconsistent with Hypothesis 1.4. Therefore, we do not find strong support for Hypotheses 1.2, 1.3 or 1.4. [86]

To conclude, we find that (Hg, Li) subjects allocate significantly more tokens to the group's account than (Hg, Hi) subjects do. In other words, when group rank is high, individual rank is significantly negatively correlated with engagement in "we-thinking". (Hg, Li) subjects allocate more tokens to the group than (Lg, Li) do, but this difference is statistically insignificant. Therefore, when group rank is low, individual rank is not significantly negatively correlated with engagement in "we-thinking". In addition, we do not find a significant correlation between group rank and engagement in "we-thinking", holding individual rank constant. [87] [88] [89]

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[86] From an affective perspective, we also investigate the relationship between group rank and self-reported group attachment (its value ranges from 1 to 7: 1 indicates the lowest level of self-reported group attachment, while 7 corresponds to the highest level). We find that when individual rank is low, group rank is significantly positively correlated with self-reported group attachment (Question 1 (relation): 4.15 vs. 3.25, p=0.006; Question 2 (identify): 5.12 vs. 3.80, p<0.001; Question 3 (sense of belonging): 3.81 vs. 2.75, p=0.001; All tests are one-sided t-tests). When individual rank is high, group rank is marginally positively correlated with self-reported group attachment (Question 1: 4.08 vs. 3.38, p=0.052; Question 2: 4.83 vs. 4.23, p=0.081; Question 3: 3.15 vs. 2.58, p=0.076; All tests are one-sided t-tests).

[87] One possible concern in using Stage 2 to manipulate subjects' group and individual ranks is that subjects' intelligence levels might confound the relationship between ranks and their subsequent allocation of tokens. Since subjects in the *Control* treatment do not know the game results in the individual battle or the group battle before the allocation task in Stage 3, we test whether intelligence is a confounding factor by examining the correlation between the number of correct answers solved by each subject in the *Control* treatment and the number of tokens they allocate to her group. The regression results (see Table 4.A.1 in Appendix 4.A) show no significant correlation between the number of correct answers and subsequent token allocations.

[88] Another possible concern is that subjects may free ride in the group battle after the individual battle. We find that there is indeed a 11% significant reduction of scores in the group battle relative to the individual battle (3.54 vs. 3.98, p<0.01). However, since we report the results from the two battles after the end of the group battle, it is impossible for subjects to infer the performances of other group members at the beginning of the group battle, so the only incentive compatible way to win the group battle is to try their best. In this sense, this reduction of score is more likely to be caused by fatigue.

[89] One can argue that an alternative source of group-esteem for those who know the painters of the five pairs of paintings may be the extent to which their painting preferences align with the name of the group they are assigned to. Our evidence against this alternative channel is that we do not find a significant correlation between the number of Klee (Kandinsky) paintings a Klee (Kandinsky) group member chose in Stage 1 and their self-reported group-esteem, holding group rank constant. See the detailed regression results in Section 4.A.5.

4.6.2. How Self-Reported Group-Esteem and Self-Esteem Affects "We-Thinking"

In Section 4.6.2, we focus on the relationship between subjects' self-reported group/self-esteem[90] and engagement in "we-thinking".

4.6.2.1. Manipulation Checks on the Correlation Between Rank and Self-Reported Esteem

Before we check the correlation between self-reported esteem and token allocation, we first do a manipulation check on the relationship between group (individual) rank and self-reported group-esteem (self-reported self-esteem) to examine whether subjects' self-reported group-esteem and self-reported self-esteem are mainly based on their group and individual ranks respectively.

Table 4.1. Correlation between self-reported group-esteem and group rank

VARIABLES	*GFeelGood*
Hg	2.470***
	(0.234)
Constant	3.045***
	(0.186)
Observations	132
R-squared	0.461

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
(1) *Hg* is a dummy variable whose value is 1 when group rank is high and 0 otherwise.
(2) *GFeelGood* indicates subjects' responses to the question about the extent to which they feel good about their group's performance in the group battle. 1 indicates that a subject strongly disagrees with the statement that she feels good about her group's performance in the group battle in Stage 2; 2 corresponds to "disagree"; 3 corresponds to "somewhat disagree"; 4 corresponds to "neutral"; 5 corresponds to "somewhat agree"; 6 corresponds to "agree"; and 7 corresponds to "strongly agree".

Results in Table 4.1 demonstrate that the self-reported extent to which subjects feel good about their group's performance is significantly positively correlated with their group rank.

[90] The value of self-reported group/self-esteem ranges from 1 to 7: 1 indicates that a subject strongly disagrees with the statement that she feels good about her group's/own performance in the group/individual battle in Stage 2; 2 corresponds to "disagree"; 3 corresponds to "somewhat disagree"; 4 corresponds to "neutral"; 5 corresponds to "somewhat agree"; 6 corresponds to "agree"; and 7 corresponds to "strongly agree".

Specifically, the reported extent of feeling good from group performance of a subject with a high group rank is 2.470 units (41.2% of the 1-7 range) higher than that of a subject with a low group rank on average.

Table 4.2. Correlation between self-reported self-esteem and individual rank

VARIABLES	*IFeelGood*
Hi	2.076***
	(0.290)
Constant	2.742***
	(0.193)
Observations	132
R-squared	0.283

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
(1) *Hi* is a dummy variable whose value is 1 when individual rank is high and 0 otherwise.
(2) *IFeelGood* indicates subjects' responses to the question about the extent to which they feel good about their individual performance in the individual battle. 1 indicates that a subject strongly disagrees with the statement that she feels good about her own performance in the individual battle in Stage 2; 2 corresponds to "disagree"; 3 corresponds to "somewhat disagree"; 4 corresponds to "neutral"; 5 corresponds to "somewhat agree"; 6 corresponds to "agree"; and 7 corresponds to "strongly agree".

Results in Table 4.2 show that the self-reported extent to which subjects feel good about their individual performance is significantly positively correlated with their individual rank. Specifically, the self-reported extent of feeling good from individual performance of a subject with a high individual rank is 2.076 units (34.6% of the 1-7 range) higher than that of a subject with a low individual rank on average.

These strong and significant correlations between self-reported group-esteem (self-esteem) and group rank (individual rank) demonstrate that their self-reported group-esteem (self-esteem) is mainly manipulated through their group rank (individual ranks).[91]

[91] As we have indicated in Footnote 25, this result is also evidence against the possible concern that subjects' self-reported group- and self-esteem might be affected by a self-justification effect from their allocation decisions in Stage 3.

4.6.2.2. The Relationship Between Self-Reported Group/Self-Esteem and "We-Thinking"

We then investigate the relationship between self-reported group/self-esteem and we-thinking. We check the correlation between the self-reported extent to which they feel good about their group/individual performance and the number of tokens they allocate to the group's account.

Table 4.3. Correlation between the self-reported group/self-esteem and token allocation

VARIABLES	Tkn passed
$GFeelGood$	0.220**
	(0.108)
$IFeelGood$	-0.230**
	(0.0991)
Constant	2.800***
	(0.504)
Observations	132
R-squared	0.046

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3 demonstrates that a one-unit increase in the self-reported extent to which subjects feel good about their group performance is significantly correlated with 0.220 more tokens they allocate to the group's account on average, holding the self-reported extent to which they feel good about their individual performance constant. [92] It also shows that a one-unit increase in the self-reported extent to which subjects feel good about their individual performance is significantly correlated with 0.230 fewer tokens they allocate to the group's account, holding the self-reported extent to which they feel good about their group performance constant. [93] These results support Hypotheses 2.1 and 2.2.[94]

[92] This implies that a 6-unit increase (from 1 to 7) in the extent to which subjects feel good about their group performance is significantly correlated with allocating 1.32 more tokens (22% tokens) to the group's account, holding the extent to which they feel good about their individual performance constant.

[93] This implies that a 6-unit increase (from 1 to 7) in the extent to which they feel good about their individual performance is significantly correlated with allocating 1.38 fewer tokens (23% tokens) to the group's account, holding the extent to which subjects feel good about their group performance constant.

[94] We also investigate the relationship between self-reported group-esteem and self-reported group attachment. We find that the self-reported extent to which subjects feel good about their group performance is significantly positively correlated with the self-reported extent to which they feel attached to the group, holding the self-reported extent to which they feel good about their individual performance constant. See Table 4.A.3. in Appendix 4.A for the detailed regression results.

Result 2.1: The self-reported extent to which subjects feel good about their group performance is significantly positively correlated with the number of tokens they allocate to the group's account, holding the self-reported extent to which they feel good about their individual performance constant.

Result 2.2: The self-reported extent to which subjects feel good about their individual performance is significantly negatively correlated with the number of tokens they allocate to the group's account, holding the self-reported extent to which they feel good about their group performance constant.

4.7. Discussion

Our experimental results provide evidence that is consistent with our predictions regarding the relationship between rank and "we-thinking": The self-reported extent to which subjects feel good about their group (individual) performance is significantly positively (negatively) correlated with their engagement in "we-thinking", holding constant the self-reported extent to which they feel good about their individual (group) performance. Individual rank is also significantly negatively correlated with engagement in "we-thinking" when group rank is high, but the correlation becomes insignificant when group rank is low and there is no significant correlation between group rank and engagement in "we-thinking".

In order to investigate why rank and self-reported esteem predict engagement in "we-thinking" differently, we construct a measure of the difference between the group-esteem proxy and self-esteem proxy. Specifically, we take the *difference* between the self-reported group-esteem and self-reported self-esteem (i.e., $\Delta FeelGood \equiv GFeelGood - IFeelGood$) and we also take the difference between group and individual rank (i.e., $\Delta Rank \equiv group\ rank - individual\ rank$). We then test whether the sign of $\Delta FeelGood$ is the same as the sign of $\Delta Rank$. [95] If these variables

[95] An advantage of focusing on the *differences* in self-reported group/self-esteem and group/individual ranks is that they reduce the dimension of variables from two to one. Recall that our predicted correlations between group rank and "we-thinking" and that

are similarly good proxies for group-esteem and self-esteem, then $\Delta FeelGood$ and $\Delta Rank$ should have the same signs depending on how subjects did in the individual and group performance tasks. Specifically, we expect that (Hg, Hi) and (Lg, Li) subjects, whose $\Delta Rank$ is 0, should have a $\Delta FeelGood$ around 0. The (Hg, Li) subjects, whose $\Delta Rank$ is positive, should have a positive $\Delta FeelGood$, while the (Lg, Hi) subjects, whose $\Delta Rank$ is negative, should have a negative $\Delta FeelGood$.

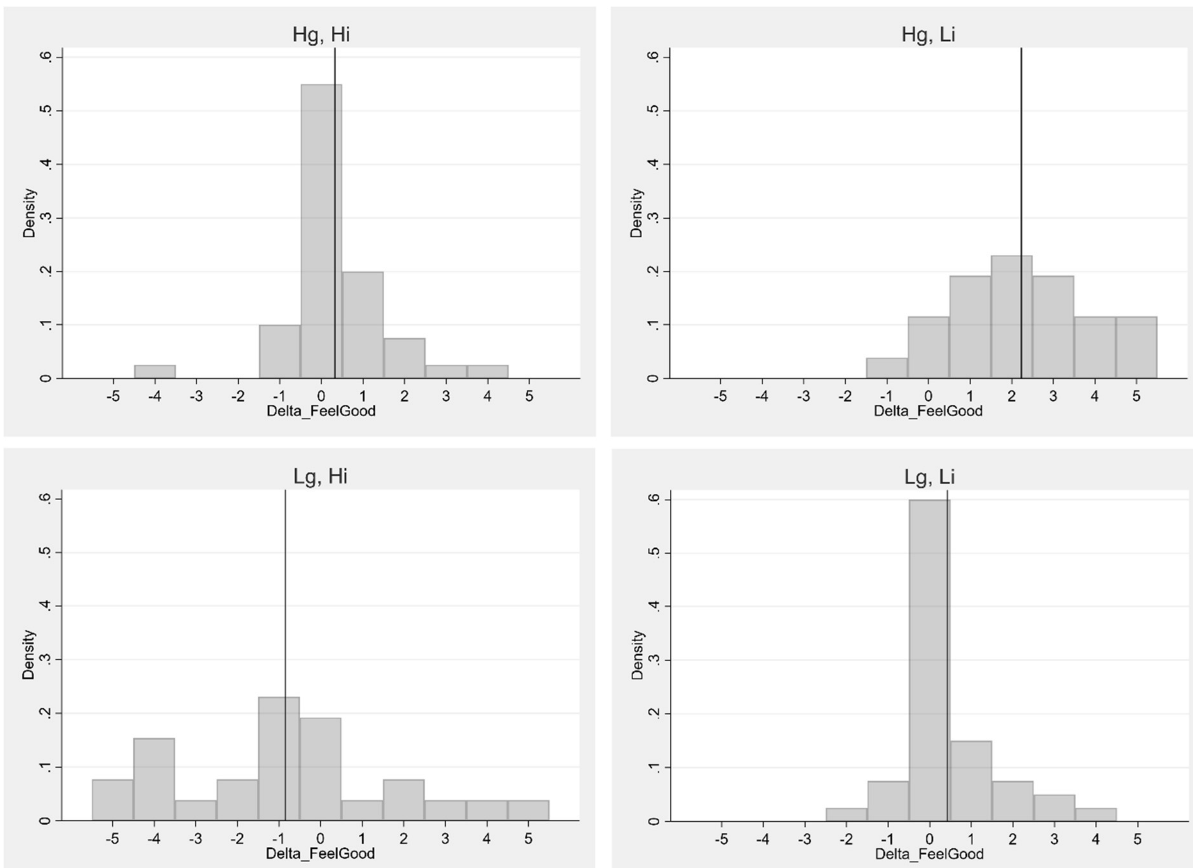

Figure 4.2. Distribution of $\Delta FeelGood$ for different group and individual ranks

Note: The long dark vertical line in each graph shows the mean of $\Delta FeelGood$.

between self-reported group-esteem and "we-thinking" are both positive. Our predicted correlations between individual rank and "we-thinking" and that between self-reported self-esteem and "we-thinking" are both negative. The opposite directions of correlations imply that the *difference* between group rank and individual rank and the *difference* between self-reported group-esteem and self-reported self-esteem should both have a positive correlation with engagement in "we-thinking". Our experimental results confirm that $\Delta FeelGood$ is significantly positively correlated with the number of tokens allocated to the group (See Table 4.A.4 in Appendix 4.A for the regression results).

Figure 4.2 demonstrates the distribution of $\Delta FeelGood$ for each rank category. We see that most (Hg, Hi) and (Lg, Li) subjects report a $\Delta FeelGood = 0$; about 85% of (Hg, Li) subjects report a $\Delta FeelGood > 0$; and less than 5% report a $\Delta FeelGood < 0$. The distribution of $\Delta FeelGood$ for (Lg, Hi) subjects, however, shows more heterogeneity. Here, about 20% of (Lg, Hi) subjects report a $\Delta FeelGood = 0$, and around 20% of them report a $\Delta FeelGood > 0$ even though their group ranks are relatively low compared to their individual ranks. For those 40% of (Lg, Hi) subjects with a $\Delta FeelGood \geq 0$, their self-reported group-esteem is not lower than their self-reported self-esteem even though their group ranks are lower than their individual ranks.

The above results demonstrate that $\Delta Rank$ matches $\Delta FeelGood$ in general. However, we also observe greater heterogeneity of $\Delta FeelGood$ among (Lg, Hi) subjects. Recall from Figure 4.1 that it is also (Lg, Hi) subjects whose numbers of tokens allocated to the group deviate most from our predictions. Thus, a possible reason for the different correlations produced by group/individual rank and self-reported group-/self-esteem, is that for (Lg, Hi) subjects, their $\Delta FeelGood$ shows more heterogeneity. This, in turn, increases the standard deviations of these subjects' token allocation.

Finally, though not anticipated by our design or prior readings, we note that there is research which suggests that when individual status is high, then people may exhibit some form of *noblesse oblige* (Homans, 1950). When a subject's individual rank stands out relative to her group rank, she is more likely to feel "noble" about herself and thus regard her personal achievement as part of her group's achievement. This might explain why there are some (Lg, Hi) subjects whose $\Delta FeelGood$ tend to be more positive than we predict.

Thus, one might conclude that the correlation between self-reported esteem and "we-thinking" is closer to our theoretical predictions because our Likert-scale questions about self-reported esteem are a direct elicitation of the esteem we defined in our theoretical model. As such, it does a better job of capturing some psychological factors than ranks do.

4.8. Conclusion

In this study we test a determinant of *when* social identity motivates "we-thinking". We extend the group/individual payoff model of R. Akerlof (2016) and test whether group-esteem and self-esteem impact an individual's willingness to maximize her group's payoff. Our model predicts that people with higher group-esteem (self-esteem) are more (less) likely to maximize their group's payoff, holding self-esteem (group-esteem) constant. We proxy for group-esteem and self-esteem using rank-based measures and self-reported measures. The experimental results using self-reported esteem are consistent with our prediction: Subjects with higher self-reported group-esteem (self-reported self-esteem) allocate more tokens to their group, holding self-reported self-esteem (self-reported group-esteem) constant. As for the rank-based measures we find weaker support: Individual rank is significantly negatively correlated with the number of tokens allocated to the group when group rank is high, but this correlation is no longer significant when group rank is low. We present some evidence to reconcile the weaker finding from rank-based measures and argue that self-reported esteem may be doing a better job capturing the psychological concept that constitutes the esteem defined in our theory.

Our study contributes to the literature of social identity and group behavior by showing when "we-thinking" is more likely to happen by using group-esteem and self-esteem, factors that are more stable and enduring than other previously explored channels such as priming or common interest/experience. Moreover, from a management perspective, our observed positive correlation between self-reported group-esteem and "we-thinking" implies that providing opportunities for groups to experience moments of positive feelings from their group membership is an effective way to motivate them to take on group or organizational goals as their own. Our finding of a negative correlation between self-reported self-esteem and "we-thinking" further suggests that it may be possible to identify group members who may be less likely to take on group goals. Moreover, when self-reported esteem is difficult to elicit, group rank and individual rank can also assist in predicting which group members are more likely to be "group-oriented". These insights can provide guidance for the optimal composition of groups in organizations and are a direction for future work in exploring reliable mechanisms that generate esteem for these groups.

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Appendices

4.A. Additional Tables

Table 4.A.1. Correlation between test score and token allocation

VARIABLES	Tkn passed
score	0.0152
	(0.134)
Constant	2.580**
	(1.109)
Observations	30
R-squared	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.A.2. Correlation between the self-reported extent to which they take pride in their group/individual performance and their allocation

VARIABLES	Tkn passed
$GPride$	0.0548
	(0.110)
$IPride$	-0.0755
	(0.0952)
Constant	2.927***
	(0.494)
Observations	132
R-squared	0.005

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.A.3. Correlation between the self-reported group/self-esteem and self-reported group attachment

VARIABLES	(1) Relation	(2) Identify	(3) Belonging
$GFeelGood$	0.314***	0.346***	0.328***
	(0.0818)	(0.0861)	(0.0878)
$IFeelGood$	-0.115	0.00525	-0.0918
	(0.0747)	(0.0790)	(0.0883)
Constant	2.796***	2.955***	1.989***
	(0.342)	(0.380)	(0.328)
Observations	132	132	132
R-squared	0.103	0.160	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.A.4. Correlation between $\Delta FeelGood$ and allocation

VARIABLES	Tkn passed
$\Delta FeelGood$	0.226***
	(0.0864)
Constant	2.758***
	(0.175)
Observations	132
R-squared	0.046

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.A.5. Correlation between painting preference and allocation

VARIABLES	(1) gFeelGood Klee members	(2) gFeelGood Kandinsky members
Klee paintings	0.0475	
	(0.197)	
Kandinsky paintings		0.167
		(0.194)
gWin	2.528***	2.239***
	(0.369)	(0.347)
Constant	2.757***	2.674***
	(0.559)	(0.868)
Observations	66	66
R-squared	0.419	0.451

Robust standard errors in parentheses

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

4.B. Experimental Instructions

[Screen 1] Introduction 1/2

Thank you for participating in this study.

This is a study in the economics of decision making. If you follow the instructions carefully, you may earn money. You will be paid your show-up fee and your earnings in cash privately, immediately after the experiment. We ask that you do not talk to any other participant during the experiment or you may be asked to leave the lab.

[Screen 2] Introduction 2/2

This experiment consists of 4 stages. At the beginning of each stage, we will walk you through the instructions of that stage.

You will be randomly assigned to interact with 5 other participants in this room today. These are the only participants you will interact with for the duration of the experiment. Therefore, when we use the word "others" or "other participants" during the experiment, we are only referring to those other 5 participants.

You will make decisions in Stage 2 and 3 that will affect your payoffs. At the end of the experiment, the computer will flip a virtual coin to determine whether your earnings from Stage 2 or Stage 3 will be used to pay you. There is a 100% chance that you will get paid, but we will use either your choice in Stage 2 or 3. This means that you should make every decision count.

[Screen 3] Stage 1: Instructions

In this stage, you will be assigned to a group. Everyone will be shown 5 pairs of paintings by two artists. You will be asked to choose which painting in each pair you prefer. You will then be classified into one of 2 groups, based on which artist you relatively prefer, compared with other people. Each group will have 3 members.

The participants you are grouped with will be the same for the rest of the experiment.

[Screen 4] Stage 1: Choose a painting 1/5

(Painting 1a) (Painting 1b)

[Screen 5] Stage 1: Choose a painting 2/5

(Painting 2a) (Painting 2b)

[Screen 6] Stage 1: Choose a painting 3/5

(Painting 3a) (Painting 3b)

[Screen 7] Stage 1: Choose a painting 4/5

(Painting 4a) (Painting 4b)

[Screen 8] Stage 1: Choose a painting 5/5

(Painting 5a) (Painting 5b)

[Screen 9] Group Assignment Result

Based on your choice, you are assigned to Group Klee/Kandinsky.

All of the 3 group members in your group relatively prefer paintings by Klee/Kandinsky, while all of the 3 members in the other group relatively prefer paintings by Kandinsky/Klee.

[Screen 10] Stage 2: Instructions

In Stage 2, you will be taking part in an exercise where you will answer questions from an intelligence test. The questions you will answer come from a test that is part of an established technique to measure the intelligence quotient (IQ).

Generally, intelligence is correlated with many factors of success in a person's life. These comprise, among other things, educational success and average life income.

Each person in the room will attempt the same test questions.

This stage consists of two competitions:

In Competition 1, each of you will be paired with a participant from the other group. You will have 5 minutes to correctly solve as many questions as you can. Within each pair, the participant who correctly solves more questions within 5 minutes wins Competition 1. If there is a tie, then the winner will be determined randomly.

In Competition 2, you will not be paired against a participant, but your Klee/Kandinsky group will compete against the Kandinsky/Klee group. You will again have 5 minutes to correctly solve as many questions as you can. At the end of Competition 2, the computer will calculate the total number of questions correctly answered by all the 3 members in each group. The group with more total correct answers wins Competition 2. If there is a tie, then the winning group will be determined randomly.

Later, you will learn whether you won or lost Competition 1 and whether your Klee/Kandinsky group won or lost Competition 2.

If Stage 2 is selected for payment, then you will receive $2.50 for each competition where you or your group won. In other words, if you won Competition 1, you will receive $2.50. If your Klee/Kandinsky group won Competition 2, then each of the 3 members in your Klee/Kandinsky group (including you) will receive $2.50. Your earnings from Competition 1 and Competition 2 will be added.

The questions you will see are part of a test used to measure a person's overall intelligence. In general for this test, the more questions you answer correctly, the higher is your measured intelligence quotient.

If you are ready to answer the test questions, please click "OK".

[Screen 11] Stage 2: Test (Competition 1)

In Competition 1, you are competing against a participant from the other group.

(Subjects finish some selected questions from Raven's Standard Progressive Matrices Test)

[Screen 12] Stage 2: Task (Competition 2)

In Competition 2, your Klee/Kandinsky group is competing against the Kandinsky/Klee group.

(Subjects finish some selected questions from Raven's Standard Progressive Matrices Test)

[Screen 13] Stage 2: You have finished Stage 2

[Control]

You have finished Stage 2.

[TreatInfo]

You have finished Stage 2.

Whether you won or lost Competition 1 against your opponent	Won/Lost
Whether your Klee/Kandinsky group won or lost Competition 2 against the Kandinsky/Klee group	Won/Lost

[Screen 14] Stage 3: Instructions

In Stage 3, you will be asked to allocate 6 tokens between your personal account and your group's account.

You can allocate all 6 tokens to your personal account, allocate some to your personal account and some to your group's account, or allocate all 6 tokens to your group's account. Please note that the value of each token you allocate to your personal account and the value of each token you allocate to your group's account are NOT the same. Each token allocated to your personal account is worth $1, while each token allocated to your group's account is worth $1.5. The money in your group's account will be evenly shared by the 3 members in your group.

After all your decisions have been submitted, we will randomly determine whether your decision or one of your 2 groupmates' decision counts. 1/3 of the time your decision will be used to determine the earnings in your group.

For example, if you decide to allocate 2 tokens to your personal account and 4 tokens to your group's account and your decision is randomly chosen, then you will receive 2 * $1 = $2 from your personal account and 4 *$1.5 / 3 = $2 from your group's account, which means that your total earnings in Stage 3 will be $2 + $2 = $4. Each of your two groupmates will receive 4 * $1.5 / 3 = $2 from the group's account.

If either of your 2 groupmates' decision is randomly chosen (let's call this groupmate A), then you and the other groupmate B will receive 1/3 of the money A allocates to the group's account, and A will receive 1/3 of the money he/she allocates to the group's account plus all the money he/she allocates to his/her personal account.

If you are ready, please click the "OK" button.

[Screen 15] Stage 3: Decision

Please drag the slider below to determine how many tokens you would like to allocate to your personal account and how many tokens you want to allocate to your group's account.

6 tokens to my personal account
0 tokens to my group's account

0 tokens to my personal account
6 tokens to my group's account

Number of token(s) I allocate to my personal account: 5
Number of token(s) I allocate to my group's account: 1

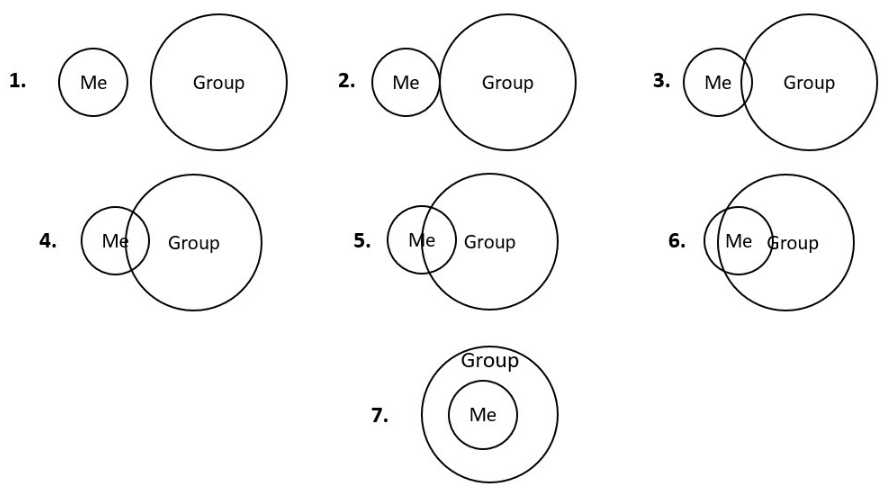
If my decision is randomly selected to determine my group's payoffs:

My payoff from my personal account ($): 5.0
My payoff from my group's account ($): 0.5
My total earnings ($): 5.5

Each groupmate's total earnings ($): 0.5

[Screen 16] Stage 4: Survey 1/3

Please indicate how you feel about the relationship between yourself and your Klee/Kandinsky group.



Please indicate how much you agree or disagree with each of the following statements. (1=strongly disagree, 2=disagree, 3=somewhat disagree, 4=neutral, 5=somewhat agree, 6=agree, 7=strongly agree)

I identify with being a member in the Klee/Kandinsky group.

I have a strong sense of belonging to the Klee/Kandinsky group.

[Screen 17] Stage 4: Survey 2/3

Please indicate how much you agree or disagree with each of the following statements. (1=strongly disagree, 2=disagree, 3=somewhat disagree, 4=neutral, 5=somewhat agree, 6=agree, 7=strongly agree)

I take pride in my performance in Competition 1 of Stage 2 (Intelligence Test).

I feel good about my performance in Competition 1 of Stage 2 (Intelligence Test).

[Screen 18] Stage 4: Survey 3/3

Please indicate how much you agree or disagree with each of the following statements. (1=strongly disagree, 2=disagree, 3=somewhat disagree, 4=neutral, 5=somewhat agree, 6=agree, 7=strongly agree)

I take pride in my Klee/Kandinsky group's performance in Competition 2 of Stage 2 (Intelligence Test)

I feel good about my Klee/Kandinsky group's performance in Competition 2 of Stage 2 (Intelligence Test).

[Screen 19] Final payment

In Stage 2, You won/lost Competition 1 against your opponent. Your Klee/Kandinsky group won/lost Competition 2 against the Kandinsky/Klee group.

In Stage 3, you/one of your groupmates' decision is randomly chosen to determine your group's payment. You/Your groupmate allocate(s) XX tokens to your/his/her personal account and XX tokens to the group's account.

Your payoff in Stage XX [2 or 3] is randomly selected.
Based on the results in Stage XX [2 or 3], your payoff in this experiment is $XX.
The show-up fee is $8.00.
Your final payoff in this experiment is $XX.

Chapter 5: Conclusion

My dissertation focuses on the role information plays in market and allocation efficiency. Chapters 2 and 3 investigate how information about product or service quality affects surplus, while Chapter 4 examines how information about an individual's social position changes her willingness to take actions that maximize the allocation efficiency within her social group.

In Chapter 2, I investigate the problem of sellers' inefficient provision of services in credence goods markets caused by information asymmetry and service outcome uncertainty. I find that most sellers provide overtreatment while most buyers request compensation when there is no external intervention, which results in a low market efficiency. I also test the effectiveness of a reputation system, which makes sellers' and buyers' history visible to each other, and a behavioral nudge, which makes sellers' efficient treatment choice and buyers' avoidance of compensation request salient. I find that the reputation system alone significantly reduces buyers' likelihood of requesting compensation, while the combination of the reputation system and the behavioral nudge significantly reduces sellers' likelihood of overtreatment, which improves total surplus in the middle and late stages of the game. This study contributes to the literature of credence goods markets in microeconomics and the literature of defensive medicine in health economics by formally modelling the interactions between sellers and buyers with incomplete information, and it provides empirical evidence from a clean experimental environment for the effectiveness of an informational and a behavioral method in order to improve total surplus. An interesting and important implication from this chapter is that the inefficiency problem in some markets is not only caused by a lack of information but also resulted from some biased social opinions. In future studies, there are two directions researchers can extend to: First, we can investigate whether people tend to have different expectations for sellers' and buyers' responsibilities and whether it leads to inefficiency in real-life markets. Second, we can explore the potential causes of these biases. One potential mechanism that may facilitate these biases can be the information asymmetry itself: when one role is considered to have an informational disadvantage, people tend to be more tolerant of uncooperative behaviors from the people in this role in order to "compensate" them for the disadvantage.

In Chapter 3, we investigate markets in which consumers' only reliable source of information of product quality is a third-party testing organization with a limited testing capacity. We design a testing mechanism for the testing organization which uses an algorithm to make full use of the limited testing capacity to maximize consumer surplus. Our experimental results show that with our mechanism, the total consumer surplus is close to the optimal level and is significantly higher than a generic testing mechanism which randomly selects products to test and reveal their qualities. This study demonstrates that we are able to maximize consumer surplus through a selection mechanism even if only a small fraction of information about product quality can be revealed. Future studies can extend the application of informational methods to concrete markets where product information is opaque. For example, the product testing mechanism can be applied to some e-commerce platforms. Based on our theoretical predictions and experimental findings from this chapter, a good testing or certification selection mechanism may help improve consumer surplus on these e-commerce platforms through two channels: First, it only provides information about products that are most preferred by consumers, which reduces consumers' cognitive load (i.e., consumers do not need to browse a large number of products and compare the information among them). Second, the mechanism pushes online merchants to compete against each other in price and quality, in order to be qualified for product information revelation.

In Chapter 4, we find that group-esteem (self-esteem), defined as an individual's positive feelings derived from her information about the relative position of her social group (herself), is correlated with her willingness to take actions that maximize the group's efficiency. Our results contribute to the literature of social identity by finding a predictor of group-regarding behavior that is more stable and has a more long-lasting effect than other commonly used factors or methods such as priming and common experiences or interests. Future studies can test the effectiveness of esteem as a predictor of group-regarding behavior among members in real-life social groups, such as companies, schools, non-governmental organizations and so on.