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

Zhewei Song[1]

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Abstract:

In credence goods markets such as healthcare service markets, when a buyer encounters a problem that needs treatment, only sellers have the expertise to determine which type of treatment is sufficient to address the buyer's problem. Although sufficient treatment maximizes buyers' expected utility, sometimes it cannot guarantee a 100% success rate. When a treatment failure happens, buyers cannot determine whether it is caused by insufficient treatment or bad luck after sufficient treatment, and they may express their dissatisfaction with sellers in costly ways by engaging in "crying behavior" that result in compensation. To avoid the costly aftermath of "crying behavior", sellers will "defend" themselves by overtreating to minimize the probability of treatment failure. However, the high cost of overtreatment incurred by both sellers and buyers will result in a Pareto-inefficient outcome, as compared to the situation where buyers do not "cry" and sellers choose sufficient treatment. This study investigates whether the market inefficiency stemming from sellers' overtreatment and buyers' crying behavior can be alleviated through a reputation system and/or a behavioral nudge. I show that when there is a reputation system which makes sellers' treatment 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 that sufficient treatment and not crying lead to a Pareto-efficient outcome, encourages them to play the Pareto-efficient strategy profile. My laboratory experiment results show that most sellers overtreat while most buyers cry when neither the reputation system nor the nudge is present. 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.

Keywords: Credence goods markets, defensive treatment, crying behavior, reputation, nudge, normative belief
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[1] Zhewei Song: School of Information, University of Michigan, 105 South State Street, Ann Arbor, MI 48109. I am grateful to Erin Krupka, David Miller, Yan Chen, Tanya Rosenblat, Alain Cohn, Stephen Leider, Manuel Hoffmann, participants of the 2021 Economic Science Association North America Conference, the 91st Annual Meeting of the Southern Economic Association, the 2022 Economic Science Association Asia-Pacific Conference, the 2022 Chinese Economist Society Annual Meeting, and of the University of Michigan School of Information Behavioral and Experimental Economics Laboratory Group for helpful discussions and comments. The author gratefully acknowledges the financial support from the Rackham Graduate Student Research Fund at the University of Michigan. The research has been approved by the University of Michigan Institutional Review Board (HUM00206935).

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 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 behaviors" 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 behaviors", defined as behaviors that express 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 behaviors, 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 behaviors 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 behaviors.

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

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

[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 behaviors. 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.

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 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. My repeated game analysis for the effectiveness of the reputation system is more comprehensive than other credence goods markets literature that discusses reputation (e.g.,

[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.
[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.

Dulleck et al. 2011).[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.

2. Literature Review

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 and Wolinsky (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 and 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 and Wolinsky, 2003; Alger and Salanie, 2004; Dulleck and Wolinsky, 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) 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. Empirical evidence of crying behaviors and defensive treatment

[10] See Section 2.3 for a detailed discussion.

[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.

Buyers' crying behaviors after a failed treatment are 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." (WHO) 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 and 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 behaviors is termed "positive defensive medicine".[13] There is ample empirical evidence showing that (positive) 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; Moser and Musacchio, 1991; Kessler and McClellan, 1998; Agarwal et al., 2019; Keane et al., 2020), European countries (Toraldo et al., 2015; Garattini and Padula, 2020) and China (He, 2014).

Although much empirical literature has demonstrated the prevalence of buyers' crying behaviors 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.

2.3. 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]

2.4. Using nudges to promote positive behavior

[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 and Vyas, 2013).

[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.

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, 2008) 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, [15] 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, 2004). Primers that trigger pro-social concepts such as morality and sharing (de Medeiros et al., 2021) or religious concepts (Shariff et al., 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 behavior is the unique equilibrium. In addition, I show how a feasible reputation system or a behavioral nudge can theoretically improve market inefficiency.

3. Theoretical Framework

3.1. Settings of the stage game

Consider a credence goods market with one seller and one buyer.[16] 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.[17] 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

[15] In behavioral economics and social psychology, this is known as descriptive social norms.
[16] The setting of this model is adapted from Dulleck et al. (2011).
[17] 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.

and 0 from a failed treatment. The buyer strictly prefers a sufficient 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.[18] 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^hq^h (overtreatment strategy), q^hq^l (sufficient treatment strategy), and q^lq^l (undertreatment strategy) and q^lq^h [19] 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 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 1 below shows the extensive form of this game.

[18] 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.

[19] 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^hq^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^hq^l means that the seller always chooses a sufficient treatment according to the problem type, so it corresponds to the sufficient treatment strategy. q^lq^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^lq^h means that the seller undertreats when it is a major problem and overtreats when it is a minor problem.

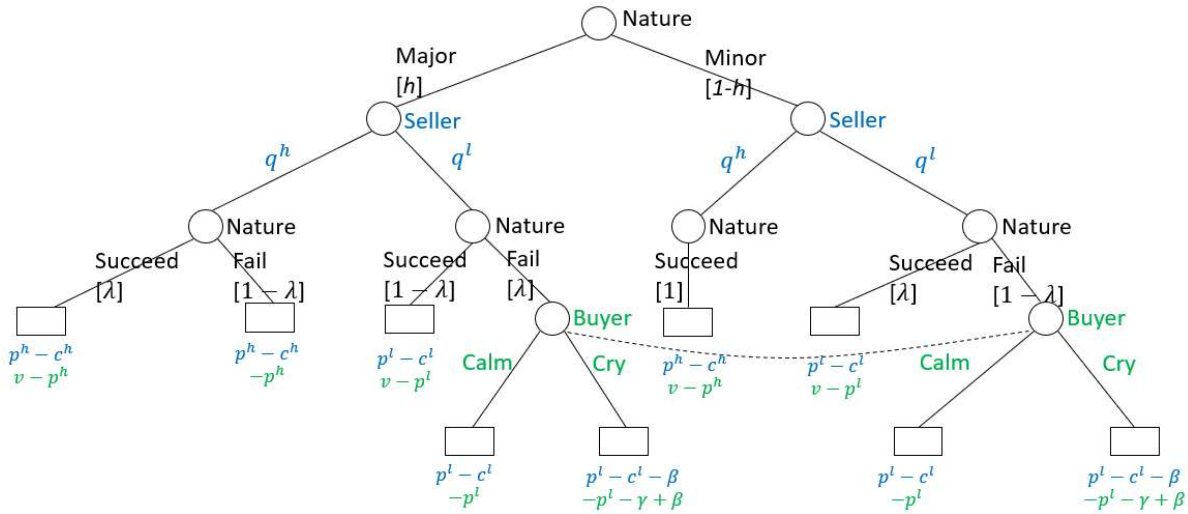

Figure 1: Extensive form of the game

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 $(q^h q^l, Calm)$.[20]

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

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.

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, so the game can be regarded as a repeated one-shot game. In this sense, playing the Pareto inefficient stage-game perfect Bayesian equilibrium in all periods (with the buyer's arbitrary belief in the information set in each period) is the only possible perfect Bayesian equilibrium in the repeated game.

3.4. How a reputation system influences behavior

[20] 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 $q^h q^h$.

3.4.1. Settings of the reputation system

Consider the game in Section 3.3 again. Different from the game in Section 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.[21]

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 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 $\boldsymbol{q^h}$ and a **s**uccessful (**f**ailed) result. LS corresponds to the seller choosing $\boldsymbol{q^l}$ and a **s**uccessful result. LFR (LFM) corresponds to the seller choosing $\boldsymbol{q^l}$, a **f**ailed result and the buyer choosing ***Cry*** (***Calm***) Table 1 demonstrates the distribution of y given each strategy profile a.

Table 1: Distribution of public signals

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

[21] 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.

anonymous so that no ID of the seller or the buyer is displayed.[22] Suppose that both sellers and buyers have a discount factor of δ.

3.4.2. Find Perfect Public Equilibria of the repeated game with the reputation system

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: [23]

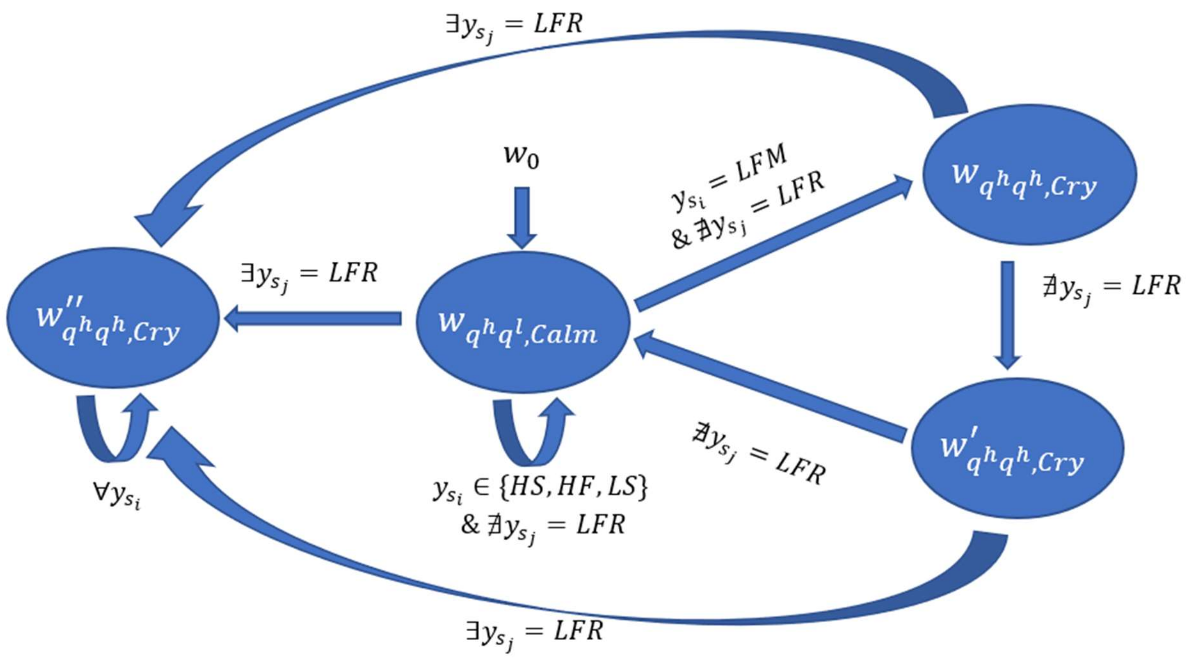

Figure 2: A 2-period punishment hybrid strategy profile

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:

[22] 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.
[23] This Pareto-improved PPE is found after I rule out some simpler strategy profiles. See Appendix C for the intuition and procedures of ruling out other simpler strategy profiles and finding this PPE.

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

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^hq^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,[24] then s_i and the next buyer matched with s_i will continue playing $(q^hq^l, Calm)$ 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^hq^h, Cry). After these two periods, s_i and the next buyer matched with s_i will return to playing $(q^hq^l, Calm)$. If there exists any pair with a public signal LFR in any period, then all sellers and buyers will perpetually switch to playing (q^hq^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.

Proposition 1: The 2-period punishment hybrid strategy profile described by the automaton in Figure 6 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 A.

Figure 3 demonstrates the ranges of h and λ that satisfy (5) and (6) when δ takes different values.

[24] Recall from Section 2.4.1 that each pair is informed of whether there exists any pair with a public signal of LFR in the previous period.

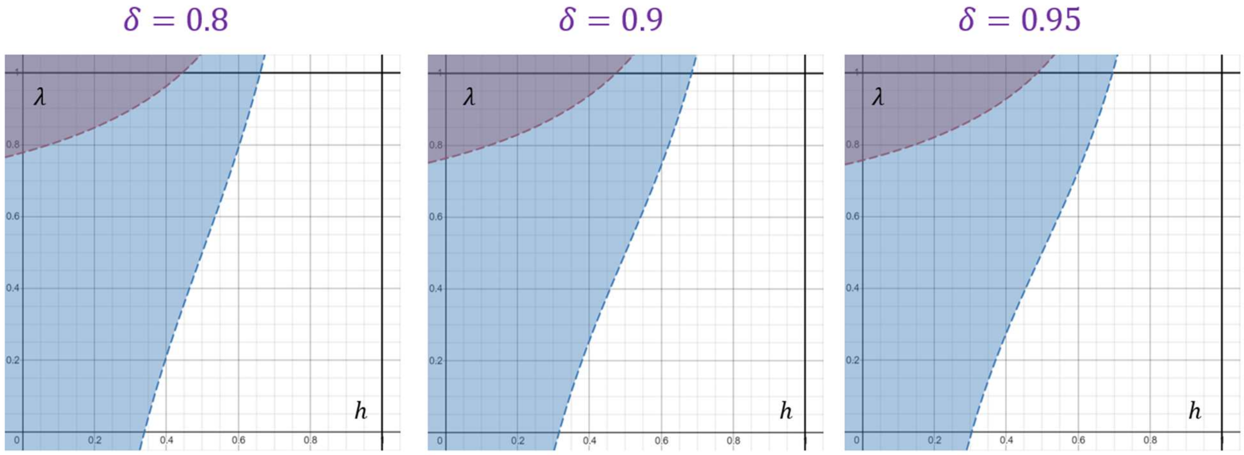

Figure 3: Ranges of h and λ that makes the 2-period punishment hybrid strategy profile a PPE

Note: The red area indicates the ranges of h and λ that satisfy (22); The blue are indicates the ranges of h and λ that satisfy (23).

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:

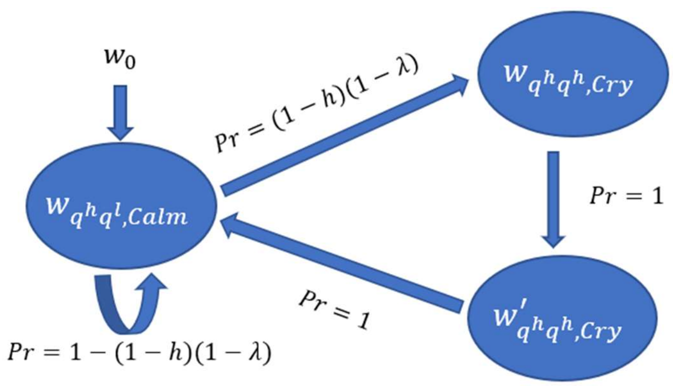

Figure 4: Transition of states if all players play the 2-period punishment hybrid strategy profile

Denote each seller's probability of being in the Pareto-efficient state $w_{q^h q^l, Calm}$ in Period t ($t = 0,\ 1,\ \ldots$) 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 $w_{q^h q^l, Calm}$ 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 $w_{q^h q^l, Calm}$ 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:

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

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

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

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

Proof: See Appendix A.

Table 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: 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**
λ	**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 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.

3.5. How a nudge changes behavior

I consider an "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,[25] 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.[26] (Schelling, 1980) Therefore, sellers and buyers are predicted to be more likely to play $(q^h q^l, Calm)$ when the nudge is implemented.

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; each buyer determines in advance whether to cry or not[27] 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%).[28]

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.

[25] 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 6.2.2 and 6.2.4.

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

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

[28] 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.

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[29]. 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 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.

After subjects finish the repeated game, sellers (buyers) are asked 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).[30] Their risk preferences are elicited through an unincentivized Holt-Laury survey (2002), and their demographic information is also collected.

Table 3 below summarizes the procedures of each condition. The experimental instructions can be found in Appendix D.[31]

Table 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

There are 5 sessions in each of the 4 conditions with a total of 160 subjects. 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

[29] Subjects are informed that every subject finishes the same comprehension questions.
[30] To avoid the subjectiveness of their judgment of the social norm, I do not ask subjects to state the most socially appropriate action they themselves should take.
[31] Appendix D is available online at https://zheweisong.github.io/files/DefensiveTreatment_Instructions.pdf

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.[32] 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.[33] 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.

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 $q^h q^h$.
> **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. The total market payoff, defined as the sum of all sellers' and buyers' payoffs in a certain period, in the *Reputation* condition should be higher than that 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.
> **Hypothesis 2.3 (Payoff in *Reputation* vs. *Baseline*):** Average total market payoff in *Reputation* is higher than that in the *Baseline* condition.

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. The total market payoff in the *Nudge* condition should also be higher than that in the *Baseline* condition. Specifically, I can write these as the following hypotheses:

[32] A few subjects are alumni of the University of Michigan.
[33] 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 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.
Hypothesis 3.3 (Payoff in *Nudge* vs. *Baseline*): Average market payoff in *Nudge* is higher than that in *Baseline*.

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. The total market payoff in the *Reputation+Nudge* condition should also be higher than that in the other three condition. Specifically, I can write these as the following hypotheses:

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 4.1.3 (Payoff in *Reputation+Nudge* vs. *Baseline*): Average market payoff in *Reputation+Nudge* is higher than that in *Baseline*.

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 4.2.3 (Payoff in *Reputation+Nudge* vs. *Reputation*): Average market payoff in *Reputation+Nudge* is higher than that in *Reputation*.

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.
Hypothesis 4.3.3 (Payoff in *Reputation+Nudge* vs. *Nudge*): Average market payoff in *Reputation+Nudge* is higher than that in *Nudge*.

6. Results

6.1. Behavior and market efficiency in the late stage (Periods 41-60)

Section 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 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 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.[34] Figure 6 shows the average total market payoff in each condition.

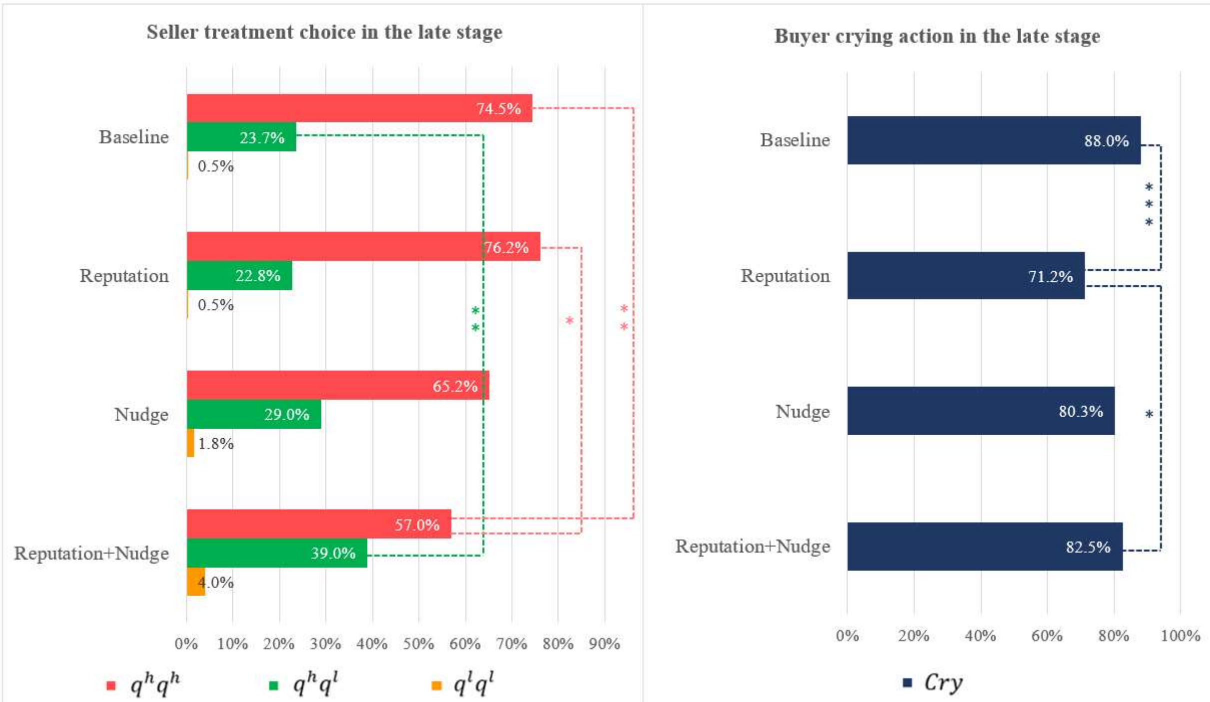

Figure 5: Proportions of sellers' treatment choices and buyer crying behavior in the late stage (Periods 41-60)

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 B.1.1 to B.1.5 in Appendix B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

[34] 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.

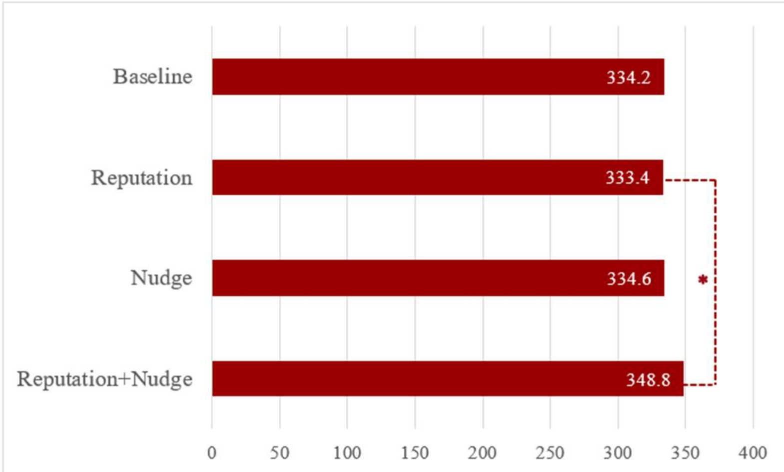

Figure 6: Average total market payoff in the late stage (Periods 41-60)

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 B.1.1 to B.1.5 in Appendix B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

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 an 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.

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 total market payoff between *Reputation* and *Baseline* (333.4 vs. 334.2, p=0.915), I do not find support for Hypothesis 2.3.

Result 2.3 (Payoff in *Reputation* vs. *Baseline*): The total market payoff in *Reputation* is not significantly different from that in *Baseline* in the late stage.

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.

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 total market payoff in *Nudge* in the late stage is 334.6, which is not significantly different from that in *Baseline* (334.2, 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.
Result 3.3 (Total market payoff in *Nudge* vs. *Baseline*): The total market payoff in *Nudge* is not significantly different from that in *Baseline* in the late stage.

Therefore, Hypotheses 3.1, 3.2 or 3.3 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.

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.

> **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*.

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). There is no significant difference in total market payoff between the two conditions (348.8 vs. 334.2, p=0.122). Thus, I do not find support for Hypotheses 4.1.2 or 4.1.3.

> **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.
> **Result 4.1.3 (Total market payoff in *Reputation+Nudge vs. Baseline*):** The total market payoff in *Reputation+Nudge* is not significantly different from that in *Baseline* in the late stage.

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 *Baseline*, and the likelihood of crying behavior in *Reputation+Nudge* is marginally significantly higher than that in *Reputation* (p=0.085). The average total market payoff in *Reputation+Nudge* is marginally significantly higher than that in *Reputation* (348.8 vs. 333.4, p=0.058).

> **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.
> **Result 4.2.3 (Total market payoff in *Reputation+Nudge vs. Reputation*):** The total market payoff in *Reputation+Nudge* is marginally significantly higher than that in *Reputation* in the late stage.

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. The average total market payoff in *Reputation+Nudge* condition is 348.8, which is not significantly different from that in *Nudge* (334.6, p=0.117). 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.
> **Result 4.3.3 (Total market payoff in *Reputation+Nudge vs. Nudge*):** The total market payoff in the *Reputation+Nudge* condition is not significantly different from that in the *Nudge* condition in the late stage.

6.1.7. Summary of behavior and market efficiency in the late stage

By examining sellers' and buyers' behavior and the total market payoff 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 total market payoff 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 total market payoff.

6.2. How sellers' and buyers' behavior change 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.

6.2.1. General change of behavior over time

Figure 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 8 shows the average total market payoff 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 total market payoffs change over the three stages.

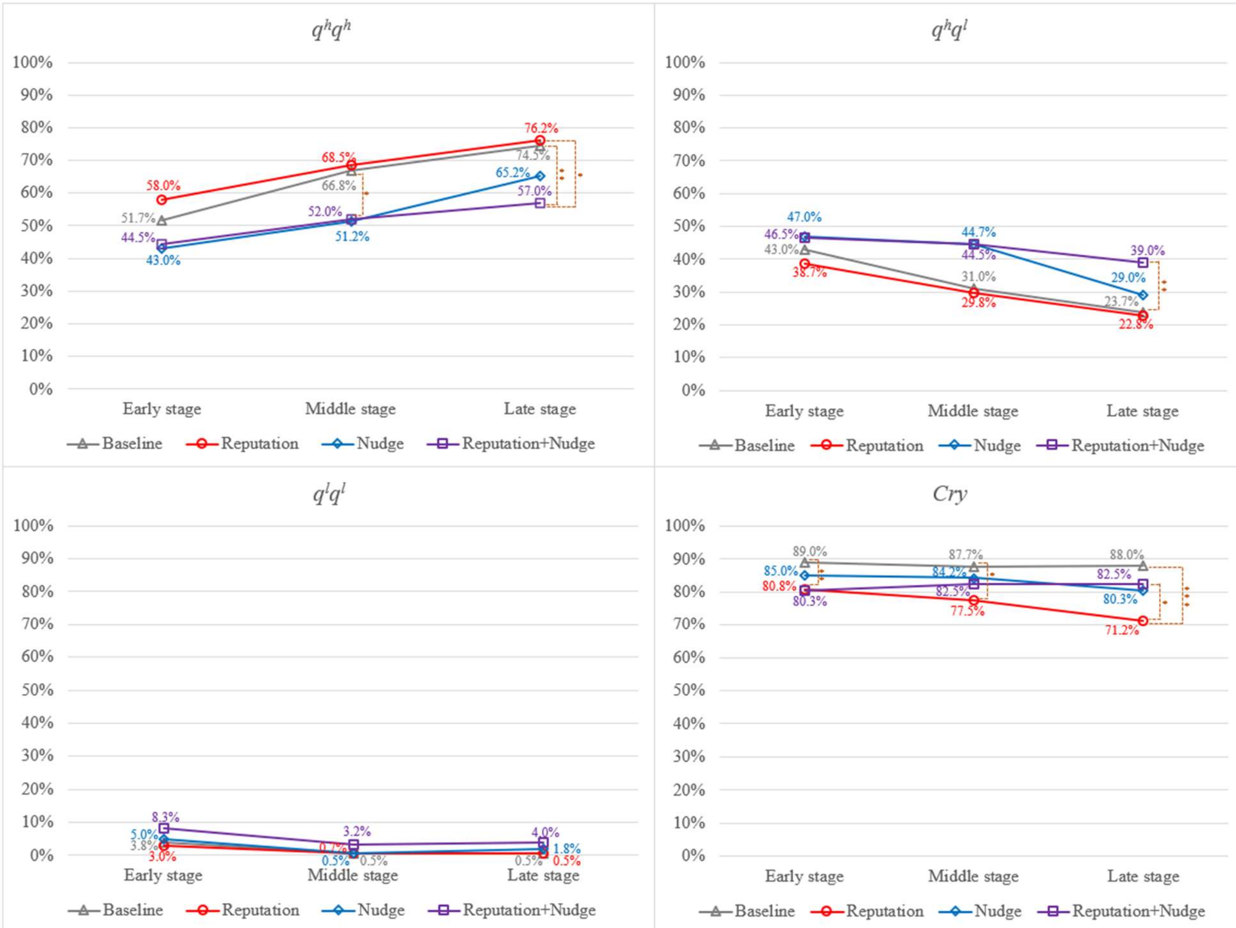

Figure 7: Proportions of sellers' treatment choices and buyer crying behavior in three stages

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 B.1.1 to B.3.5 in Appendix B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

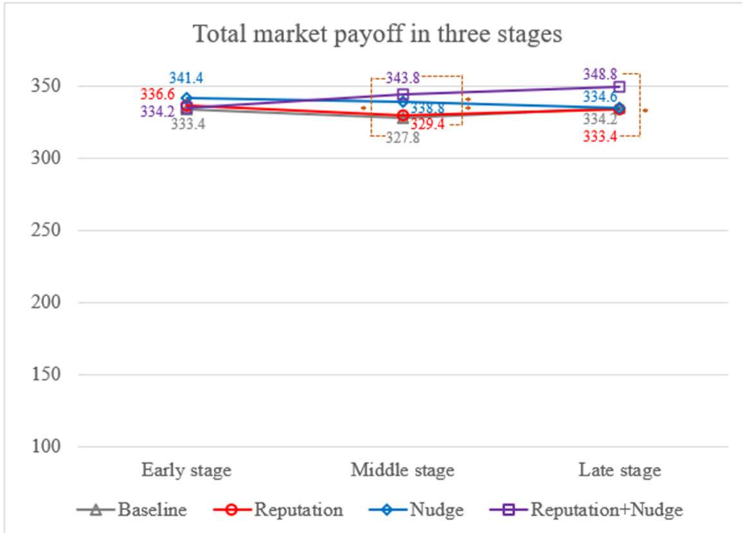

Figure 8: Total market payoff in three stages

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 B.1.1 to B.3.5 in Appendix B for detailed regression results.
2. ***: p<0.01; **: p<0.05; *: p<0.10.

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

6.2.1. *Reputation vs. Baseline*

Figure 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 8 shows that the difference in total market payoff between the two conditions is not significant in all three stages (Early stage: 336.6 vs. 333.4, p=0.837; Middle stage: 329.4 vs. 327.8, p=0.837; Late stage: 333.4 vs. 334.2, p=0.915).

The regression results in Table 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 total market payoff over time in *Baseline* (Column 5, coefficient = -0.091, p=0.732), and the change rate of total market payoff in *Reputation* is not significantly different from that in *Baseline* (Column 5, coefficient = -0.087, p=0.829).

Table 4: Time trends of likelihoods of sellers' treatment choices and total market payoffs: *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) Total market payoff
Reputation	1.035	-0.660	-0.450	-1.972**	3.977
	(1.041)	(0.994)	(1.492)	(0.901)	(17.77)
Period	0.062***	-0.052***	-0.068**	-0.003	-0.091
	(0.016)	(0.017)	(0.032)	(0.007)	(0.264)
Period x Reputation	-0.027	0.022	0.005	-0.014	-0.087
	(0.021)	(0.021)	(0.066)	(0.012)	(0.401)
Constant	-0.546	-0.036	-4.678***	5.227***	334.6***
	(0.780)	(0.752)	(0.989)	(0.833)	(12.19)
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*.

Result 5.3 (Time trends of total market payoff in *Reputation vs. Baseline*): The difference in total market payoff between *Baseline* and *Reputation* is not significant in all three stages. The total market payoff in *Baseline* does not significantly change over time, and the change rate in *Reputation* is not significantly different from that in *Baseline*.

6.2.2. *Nudge vs. Baseline*

Figure 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 8 demonstrates that the difference in total market payoff between the two conditions is not significant in all three stages (Early stage: 341.4 vs. 333.4, p=0.617; Middle stage: 338.8 vs. 327.8, p=0.193; Late stage: 334.6 vs. 334.2, p=0.962).

The regression results in Table 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 total market payoff in *Nudge* is not significantly different from that in *Baseline* (Column 5, coefficient = -0.218, p=0.644).

Table 5: Time trends of likelihoods of sellers' treatment choices and total market payoffs: *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) Total market payoff
Nudge	-0.971	0.700	-0.392	-1.365	13.11
	(1.238)	(1.207)	(1.527)	(1.121)	(19.45)
Period	0.063***	-0.052***	-0.068**	-0.003	-0.091
	(0.017)	(0.017)	(0.032)	(0.007)	(0.264)
Period x Nudge	-0.008	0.009	0.023	-0.012	-0.218
	(0.022)	(0.023)	(0.055)	(0.013)	(0.471)
Constant	-0.481	-0.139	-4.723***	5.691***	334.6***
	(0.826)	(0.785)	(1.022)	(1.035)	(12.19)
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*.

Result 6.3 (Time trends of total market payoff in *Nudge vs. Baseline*): The difference in total market payoff between *Baseline* and *Nudge* is not significant in all three stages. The change rate of total market payoff in *Nudge* is not significantly different from that in *Baseline*.

6.2.3. *Reputation+Nudge vs. Baseline*

Figure 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 8 shows that the difference in total market payoff is insignificant in the early stage (334.2 vs. 333.4, p=0.962) or late stage (348.8 vs. 334.2, p=0.122) but is marginally significantly different in the middle stage (343.8 vs. 327.8, p=0.053).

The regression results in Table 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); The decline rate of $q^h q^l$ in *Reputation+Nudge* is marginally significantly slower than that in *Baseline* (Column 2, coefficient = 0.037). There is no significant difference in the decrease rate of $q^l q^l$ between the two conditions (Column 3, coefficient = 0.039). There is no significant difference in the change rate of crying behavior (Column 4, coefficient = 0.006) or the change rate of total market payoff (Column 5, coefficient = 0.297) between the two conditions.

Table 6: Time trends of likelihoods of sellers' treatment choices and total market payoffs: *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) Total market payoff
Reputation+Nudge	0.020	-0.228	0.496	-1.038	1.419
	(0.999)	(0.925)	(1.003)	(1.129)	(19.69)
Period	0.062***	-0.052***	-0.068**	-0.004	-0.091
	(0.016)	(0.017)	(0.032)	(0.007)	(0.264)
Period x Reputation+Nudge	-0.039**	0.037*	0.039	0.006	0.297
	(0.020)	(0.020)	(0.034)	(0.015)	(0.434)
Constant	-0.546	-0.024	-4.510***	6.194***	334.6***
	(0.779)	(0.749)	(0.881)	(1.196)	(12.19)
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*.

Result 7.3 (Time trends of total market payoff in *Reputation+Nudge vs. Baseline*): The difference in total market payoff in *Reputation+Nudge* is marginally significantly higher than that in *Baseline* in the middle stage, but the difference is insignificant in the early or late stages. The change rate of total market payoff in *Reputation+Nudge* is not significantly different from that in *Baseline*.

6.2.4. *Reputation+Nudge vs. Reputation*

Figure 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 8 shows that the difference in total market payoff is insignificant in the early (334.2 vs. 336.6, p=0.898), significant in the middle stage (343.8 vs. 329.4, p=0.035) and marginally significant in the late stage (348.8 vs. 333.4, p=0.058).

The regression results in Table 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 total market payoff in *Reputation* over time (Column 5, coefficient = -0.177, p=0.557), and the change rate in *Reputation+Nudge* is not significantly different from that in *Reputation* (Column 5, coefficient = 0.383, p=0.403).

Table 7: Time trends of likelihoods of sellers' treatment choices and total market payoffs: *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) Total market payoff
Nudge	-0.929	0.387	1.008	0.762	-2.558
	(0.874)	(0.791)	(1.442)	(1.032)	(20.16)
Period	0.034***	-0.030**	-0.063	-0.017*	-0.177
	(0.013)	(0.013)	(0.057)	(0.010)	(0.302)
Period x Nudge	-0.012	0.016	0.034	0.020	0.383
	(0.017)	(0.017)	(0.059)	(0.017)	(0.458)
Constant	0.383	-0.588	-5.158***	3.127***	338.5***
	(0.650)	(0.618)	(1.331)	(0.747)	(12.94)
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*.

Result 8.3 (Time trends of total market payoff in *Reputation+Nudge vs. Reputation*): The difference in total market payoff between *Reputation* and *Reputation+Nudge* is not significant in the early stage, but the total market payoff in *Reputation+Nudge* becomes significantly higher than that in *Reputation* in the middle stage and marginally significantly higher in the late stage. The change rate of total market payoff in *Reputation+Nudge* is not significantly different from that in *Reputation*.

6.2.5. *Reputation+Nudge vs. Nudge*

Figure 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 8 demonstrates that the difference in total market payoff between the two conditions is not significant in all three stages (Early stage: 334.2 vs. 341.4, p=0.706; Middle stage: 343.8 vs. 338.8, p=0.509; Late stage: 348.8 vs. 334.6, likelihood difference p=0.117).

The regression results in Table 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 total market payoff in *Reputation+Nudge* is not significantly different from that in *Nudge* (Column 5, coefficient = 0.514, p=0.324).

Table 8: Time trends of likelihoods of sellers' treatment choices and total market payoffs: *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) Total market payoff
Reputation	0.921	-0.846	0.948	0.183	-11.69
	(1.078)	(1.039)	(1.431)	(1.180)	(21.65)
Period	0.054***	-0.043***	-0.046	-0.016	-0.308
	(0.014)	(0.016)	(0.045)	(0.011)	(0.391)
Period x Reputation	-0.031*	0.029	0.016	0.018	0.514
	(0.018)	(0.019)	(0.047)	(0.017)	(0.521)
Constant	-1.438*	0.562	-5.119***	4.142***	347.7***
	(0.866)	(0.862)	(1.222)	(0.800)	(15.16)
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*.

Result 9.3 (Time trends of total market payoff in *Reputation+Nudge vs. Nudge*): The difference in total market payoff between *Nudge* and *Reputation+Nudge* is not significant in all three stages. The change rate of total market payoff in *Reputation+Nudge* is not significantly different from that in *Nudge*.

6.2.6. Summary of how sellers' and buyers' behavior change over time

In Subsection 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 total market payoff 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.

6.3. Analysis of buyers' repeated game strategy: How buyers react to sellers' treatment history

The analysis in Section 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.[35] 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*.

[35] 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.

Table 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 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).[36]

Result 10 (Correlation between buyers' crying behavior and the matched seller's treatment choice in *Reputation* and *Reputation+Nudge*): 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.

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 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

[36] 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 B.4.1.

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).

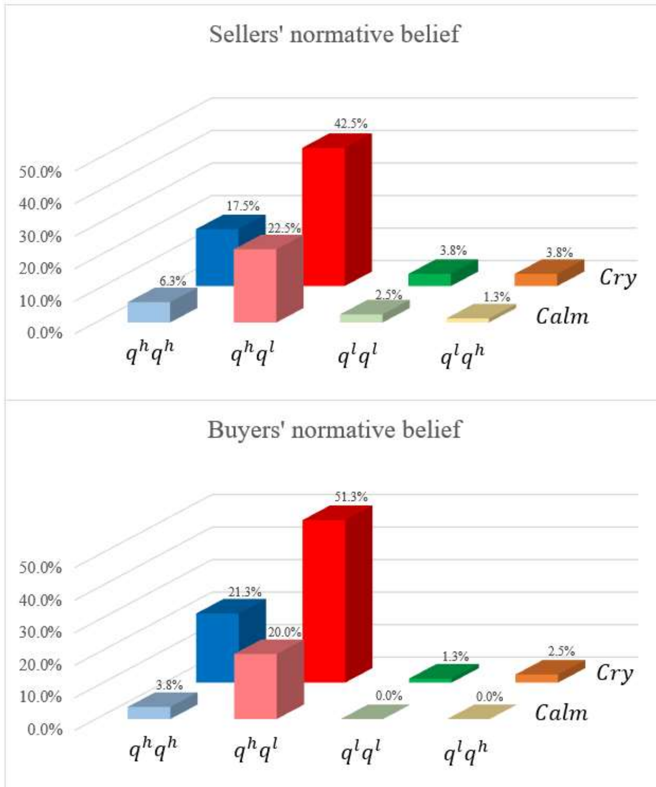

Figure 9: Subjects' belief about the normative behavior

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 $q^h q^l$.

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 sellers' behavior is closer to my predictions than buyers' behavior is. The majority of sellers and buyers believe that it is most socially appropriate for sellers to choose the sufficient treatment strategy and most socially appropriate for buyers to engage in crying behavior. Their belief echoes the fact that around 50% sellers start with the sufficient treatment strategy and most buyers start with crying behavior. Second, 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. 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. Third, 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.

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Appendix A: Proof of Propositions

A.1. Proposition 1: The 2-period punishment hybrid strategy profile described by the automaton in Figure 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 simply 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 $w''_{HH,R}$.

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

A.1.1.1. The seller

The seller's average discounted payoffs 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:

$$\begin{aligned} V_s(w_{HH,R}) &= (1-\delta)\pi^h + \delta\big[(1-\delta)\pi^h + \delta V_s(w_{HL,M})\big] = (1-\delta)\pi^h + \delta(1-\delta)\pi^h + \delta^2 V_s(w_{HL,M}) \\ &= (1+\delta)(1-\delta)\pi^h + \delta^2 V_s(w_{HL,M}) \end{aligned} \quad (10)$$

Plug (10) into (7):

$$\begin{aligned} V_s(w_{HL,M}) &= (1-\delta)[h\pi^h + (1-h)\pi^l] \\ &\quad + \delta\big[(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h + \delta^2(1-h)(1-\lambda)V_s(w_{HL,M}) \\ &\quad + \big(1-(1-h)(1-\lambda)\big)V_s(w_{HL,M})\big] \\ &= (1-\delta)[h\pi^h + (1-h)\pi^l] \\ &\quad + \delta\left[(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h + V_s(w_{HL,M})[\delta^2(1-h)(1-\lambda) + 1 - (1-h)(1-\lambda)]\right] \\ &= (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta(1-h)(1-\lambda)(1+\delta)(1-\delta)\pi^h \\ &\quad + \delta[1-(1+\delta)(1-\delta)(1-h)(1-\lambda)]V_s(w_{HL,M}) \end{aligned}$$

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

$$\begin{aligned} \Rightarrow V_s(w_{HL,M}) &= \frac{h\pi^h + (1-h)\pi^l + \delta(1+\delta)(1-h)(1-\lambda)\pi^h + \pi^h - \pi^h}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\ &= \pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \end{aligned} \quad (11)$$

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

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

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

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

$$\begin{aligned}
\Rightarrow V_s(w_{HL,M}) - g_s(w_{HL,M}, LL) \\
&= (1-\delta)(-h\Delta\pi) \\
&+ \delta\big\{[(1-h)(1-\lambda) - 1 + (1-h)\lambda + (1-\lambda)h]V_s(w_{HH,R}) \\
&+ [1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h]V_s(w_{HL,M})\big\} \\
&= (1-\delta)(-h\Delta\pi) \\
&+ \delta\left\{[(1-h)(1-\lambda) - 1 + (1-h)\lambda + (1-\lambda)h]\left(\pi^h + \frac{\delta^2(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right)\right. \\
&\left.+ [1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h]\left(\pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right)\right\} \\
&= (1-\delta)(-h\Delta\pi) + \delta[1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h] \\
&\cdot\frac{(1-\delta^2)(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= (1-\delta)\Delta\pi\left[\frac{\delta[1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h](1+\delta)(1-h)}{1+\delta(1+\delta)(1-h)(1-\lambda)} - h\right] \\
&= (1-\delta)\Delta\pi \\
&\cdot\frac{\delta(1+\delta)(1-h)[1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h] - h - h\delta(1+\delta)(1-h)(1-\lambda)}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= (1-\delta)\Delta\pi\cdot\frac{\delta(1+\delta)(1-h)[1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h-2(1-\lambda)h] - h}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= (1-\delta)\Delta\pi\cdot\frac{\delta(1+\delta)(1-h)(2h\lambda-h) - h}{1+\delta(1+\delta)(1-h)(1-\lambda)}
\end{aligned}$$

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

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 payoff of taking a one-shot deviation to LH in the state $w_{HL,M}$ is:

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

$$\begin{aligned}
\Rightarrow V_s(w_{HL,M}) - g_s(w_{HL,M}, LH)& \\
&= (1-\delta)[h(-\Delta\pi) + (1-h)\Delta\pi] \\
&\quad + \delta\{[(1-h)(1-\lambda) - h\lambda]V_s(w_{HH,R}) + [1-(1-h)(1-\lambda) - 1 + h\lambda]V_s(w_{HL,M})\} \\
&= (1-\delta)(1-2h)\Delta\pi \\
&\quad + \delta\{(1-h)(1-\lambda)V_s(w_{HH,R}) - h\lambda V_s(w_{HH,R}) + h\lambda V_s(w_{HL,M}) - (1-h)(1-\lambda)V_s(w_{HL,M})\} \\
&= (1-\delta)(1-2h)\Delta\pi + \delta\left\{(1-h)(1-\lambda)\left(V_s(w_{HH,R} - w_{HL,M})\right) + h\lambda\left(V_s(w_{HL,M}) - V_s(w_{HH,R})\right)\right\} \\
&= (1-\delta)(1-2h)\Delta\pi + \delta\left(V_s(w_{HH,R}) - V_s(w_{HL,M})\right)\left(h\lambda - (1-h)(1-\lambda)\right) \\
&= (1-\delta)(1-2h)\Delta\pi + \frac{\delta(1-\delta^2)(1-h)\Delta\pi}{1+\delta(1+\delta)(1-h)(1-\lambda)} \cdot (h+\lambda-1) \\
&= \Delta\pi(1-\delta)\left[(1-2h) + \frac{\delta(1+\delta)(1-h)(h+\lambda-1)}{1+\delta(1+\delta)(1-h)(1-\lambda)}\right] \\
&= \Delta\pi(1-\delta) \cdot \frac{[\delta(1+\delta)(1-h)(h+\lambda-1) + (1-2h)[1+\delta(1+\delta)(1-h)(1-\lambda)]}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= \Delta\pi(1-\delta) \cdot \frac{\delta(1+\delta)(1-h)(h+\lambda-1) + 1 - 2h + (1-2h)\delta(1+\delta)(1-h)(1-\lambda)}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= \Delta\pi(1-\delta) \cdot \frac{\delta(1+\delta)(1-h)\big(h+\lambda-1+(1-2h)(1-\lambda)\big) + 1 - 2h}{1+\delta(1+\delta)(1-h)(1-\lambda)} \\
&= \Delta\pi(1-\delta) \cdot \frac{\delta(1+\delta)(1-h)h(2\lambda-1) + (1-2h)}{1+\delta(1+\delta)(1-h)(1-\lambda)}
\end{aligned} \tag{19}$$

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:

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

A.1.1.2. The buyer

The buyer's average discounted payoff 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.[37]

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

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

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

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

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

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

---

[37] $\psi_1^{t+1} = [1 \quad 0 \quad 0]\boldsymbol{M}^t \begin{bmatrix}1\\0\\0\end{bmatrix}$, $\psi_2^{t+1} = [1 \quad 0 \quad 0]\boldsymbol{M}^t \begin{bmatrix}0\\1\\0\end{bmatrix}$, 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.

$$(25)$$

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

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

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

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

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:

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

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

$$
\begin{aligned}
V_b^t(w_{HH,R}) &= (1-\delta)\pi_{HH,R} + \delta\left[(1-\delta)\pi_{HH,R} + \delta V_b^{t+2}(w_{HH,R}) + \delta\psi_1^{t+2}\Delta\pi_{MR}\right] + \delta\psi_1^{t+1}\Delta\pi_{MR} \\
&= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R} + \delta^2 V_b^{t+2}(w_{HH,R}) + \delta^2\psi_1^{t+2}\Delta\pi_{MR} + \delta\psi_1^{t+1}\Delta\pi_{MR} \\
&= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R} + \delta^2\left[(1-\delta)\pi_{HH,R} + \delta V_b^{t+3}(w_{HH,R}) + \delta\psi_1^{t+3}\Delta\pi_{MR}\right] + \delta^2\psi_1^{t+2}\Delta\pi_{MR} \\
&\quad + \delta\psi_1^{t+1}\Delta\pi_{MR} \\
&= (1-\delta)\pi_{HH,R} + \delta(1-\delta)\pi_{HH,R} + \delta^2(1-\delta)\pi_{HH,R} + \delta^3 V_b^{t+3}(w_{HH,R}) + \delta^3\psi_1^{t+3}\Delta\pi_{MR} + \delta^2\psi_1^{t+2}\Delta\pi_{MR} \\
&\quad + \delta\psi_1^{t+1}\Delta\pi_{MR} = (1-\delta)\pi_{HH,R}(\delta^0+\delta^1+\delta^2) + \delta^3 V_b^{t+3}(w_{HH,R}) + \Delta\pi_{MR}(\delta\psi_1^{t+1} + \delta^2\psi_1^{t+2} + \delta^3\psi_1^{t+3}) \\
&= (1-\delta)\pi_{HH,R}(\delta^0+\delta^1+\delta^2+\cdots+\delta^n) + \delta^{n+1}V_b^{t+n+1}(w_{HH,R}) \\
&\quad + \Delta\pi_{MR}(\delta\psi_1^{t+1} + \delta^2\psi_1^{t+2} + \cdots + \delta^{n+1}\psi_1^{t+n+1}) \\
&= (1-\delta)\pi_{HH,R}\cdot\lim_{k\to\infty}\sum_{l=0}^{k}\delta^l + \lim_{k\to\infty}\delta^{k+1}\cdot\lim_{k\to\infty}V_b^{t+k+1}(w_{HH,R}) + \Delta\pi_{MR}\cdot\lim_{k\to\infty}\sum_{l=0}^{k}\delta^{l+1}\psi_1^{t+l+1} \\
&= (1-\delta)\pi_{HH,R}\cdot\frac{1}{1-\delta} + 0 + \Delta\pi_{MR}\cdot\lim_{k\to\infty}\sum_{l=0}^{k}\delta^{l+1}\psi_1^{t+l+1} = \pi_{HH,R} + \Delta\pi_{MR}\cdot\sum_{l=0}^{\infty}\delta^{l+1}\psi_1^{t+l+1} > \pi_{HH,R}
\end{aligned}
\tag{29}
$$

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).

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

A.1.2.1. The seller

The seller's average discounted payoff 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 payoffs of taking a one-shot deviation to HL, LL and LH are:

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

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

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

We can easily know that $V_s(w_{HH,R})$ is the highest among these four continuation payoffs, 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.

A.1.2.2. The buyer

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

$$V_b^t(w_{HH,R}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v-p^h)] + \delta\left[\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\right] \quad (32)$$

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

$$\begin{aligned} g_b^t(w_{HH,R}, M) &= (1-\delta)[h(\lambda v - p^h) + (1-h)(v-p^h)] + \delta\left[\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\right] \\ &= V_b^t(w_{HH,R}) \end{aligned} \quad (33)$$

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

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

A.1.3.1. The seller

We know that:

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

Therefore:

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

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

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

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

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

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

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

We can easily know that $V_s(w'_{HH,R})$ is the highest among these four continutation payoffs, 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.

A.1.3.2. The buyer

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

$$V_b^t(w'_{HH,R}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v-p^h)] + \delta\left[\psi_1^{t+1}V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1})V_b^{t+1}(w_{HH,R})\right] \quad (34)$$

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

$$g_b^t(w'_{HH,R}, M) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta[\psi_1^{t+1} V_b^{t+1}(w_{HL,M}) + (1-\psi_1^{t+1}) V_b^{t+1}(w_{HH,R})]$$
$$= V_b^t(w'_{HH,R}) \tag{35}$$

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

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

A.1.4.1. The seller

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

$$V_s(w''_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w''_{HH,R}) \tag{36}$$

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

$$g_s(w''_{HH,R}, HL) = (1-\delta)[h\pi^h + (1-h)(\pi^l - (1-\lambda)\beta)] + \delta V_s(w''_{HH,R}) \tag{37}$$
$$g_s(w''_{HH,R}, LL) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)(\pi^l - (1-\lambda)\beta)] + \delta V_s(w''_{HH,R}) \tag{38}$$
$$g_s(w''_{HH,R}, LH) = (1-\delta)[h(\pi^l - \lambda\beta) + (1-h)\pi^h] + \delta V_s(w''_{HH,R}) \tag{39}$$

We can easily know that $V_s(w''_{HH,R})$ is the highest among these four average discounted payoffs, 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.

A.1.4.2. The buyer

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

$$V_b^t(w''_{HH,R}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta V_b^t(w''_{HH,R}) \tag{40}$$

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

$$g_b^t(w''_{HH,R}, M) = (1-\delta)[h(\lambda v - p^h) + (1-h)(v - p^h)] + \delta V_b^t(w''_{HH,R}) = V_b^t(w''_{HH,R}) \tag{41}$$

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:

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

■

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:

$$M_0 = [1 \quad 0 \quad 0]$$
$$M_1 = [y \quad x \quad 0]$$
$$M_2 = [y^2 \quad yx \quad x]$$
$$M_3 = [y^3 + x \quad y^2 x \quad yx]$$
$$\ldots$$

$$M_t = [1 \quad 0 \quad 0]\begin{pmatrix} y & x & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix}^t \tag{42}$$

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

Therefore, I can derive the recursive relation for ψ_t:

$$\psi_t = y\psi_{t-1} + x\psi_{t-3} \quad (t \geq 3) \tag{43}$$

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

$$-k^3 + yk^2 + 0k + x = 0 \tag{44}$$

This equation has the following three roots:

$$k_1 = 1$$

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

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

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

$$\psi_t = A + r^t(C_1 \cos t\theta + C_2 \sin t\theta) \tag{45}$$

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

$$r = |k_2| = |k_3| = \sqrt{S_1^2 + S_2^2 - \frac{y}{3}(S_1 + S_2) - S_1 S_2 + \frac{y^2}{9}} \tag{46}$$

$$S_1 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} + \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}}, S_2 = \sqrt[3]{\frac{y^3}{27} + \frac{x}{2} - \sqrt{\left(\frac{y^3}{27} + \frac{x}{2}\right)^2 + \left(-\frac{y^2}{9}\right)^3}} \tag{47}$$

$$\theta = \arctan \frac{\frac{\sqrt{3}}{2}(S_1 - S_2)}{\frac{y}{3} - \frac{1}{2}(S_1 + S_2)} + \pi \tag{48}$$

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:

$$\begin{cases} A + cos0 \cdot C_1 + sin0 \cdot C_2 = 1 \\ A + r\cos\theta \cdot C_1 + r\sin\theta \cdot C_2 = y \\ A + r^2\cos 2\theta \cdot C_1 + r^2 \sin 2\theta = y^2 \end{cases} \tag{49}$$

I get:

$$
\begin{cases}
A = 1 - \left(\dfrac{y-1}{r\cos\theta - 1} - \dfrac{C_2 r\sin\theta}{r\cos\theta - 1}\right) \\
C_1 = \dfrac{y-1}{r\cos\theta - 1} - \dfrac{C_2 r\sin\theta}{r\cos\theta - 1} \\
C_2 = \dfrac{\dfrac{y^2-1}{r^2\cos 2\theta - 1} - \dfrac{y-1}{r\cos\theta - 1}}{\dfrac{r^2\sin 2\theta}{r^2\cos 2\theta - 1} - \dfrac{r\sin\theta}{r\cos\theta - 1}}
\end{cases} \tag{50}
$$

Therefore, I conclude that:

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

■

Appendix B: Additional Tables

Table 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) Total market payoff
Reputation	-0.638	0.956	-0.0156	-2.553***	-0.800
	(1.034)	(1.040)	(3.401)	(0.948)	(7.454)
Constant	3.222***	-3.646***	-9.789**	5.114***	334.2***
	(0.937)	(0.990)	(4.792)	(0.979)	(6.265)
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 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) Total market payoff
Nudge	-2.009	1.795	1.757	-1.185	0.400
	(1.502)	(1.627)	(1.827)	(1.053)	(8.465)
Constant	4.004***	-4.723***	-8.226***	6.680***	334.2***
	(1.250)	(1.538)	(2.035)	(2.274)	(6.265)
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 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) Total market payoff
Reputation+Nudge	-2.761**	2.600**	2.361	-0.756	14.60
	(1.230)	(1.192)	(2.939)	(0.942)	(9.437)
Constant	3.378***	-3.898***	-9.486***	5.654***	334.2***
	(0.967)	(1.020)	(2.794)	(1.198)	(6.265)
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 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) Total market payoff
Nudge	-1.718*	1.283	2.361	1.689*	15.40*
	(0.951)	(0.931)	(2.939)	(0.980)	(8.131)
Constant	2.255***	-2.309***	-9.486***	2.319***	333.4***
	(0.664)	(0.654)	(2.794)	(0.803)	(4.039)
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 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) Total market payoff
Reputation	-1.024	1.070	0.502	0.320	14.20
	(1.133)	(1.111)	(1.659)	(1.009)	(9.066)
Constant	1.623*	-2.285***	-6.886***	4.459***	334.6***
	(0.849)	(0.840)	(1.391)	(1.068)	(5.692)
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 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) Total market payoff
Reputation	0.799	-0.475	-0.866	-1.819**	3.200
	(0.894)	(0.818)	(1.184)	(0.901)	(15.52)
Constant	0.00551	-0.451	-5.057***	4.436***	333.4***
	(0.673)	(0.619)	(0.923)	(0.854)	(9.459)
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 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) Total market payoff
Nudge	-0.719	0.408	-1.339	-1.272	8
	(1.018)	(0.967)	(1.784)	(0.991)	(15.98)
Constant	-0.0249	-0.482	-5.880***	5.424***	333.4***
	(0.718)	(0.654)	(1.325)	(1.188)	(9.459)
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 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) Total market payoff
Reputation+Nudge	-0.309	0.114	0.856	-1.448	0.800
	(0.846)	(0.725)	(0.897)	(0.910)	(16.98)
Constant	0.00729	-0.438	-4.778***	5.494***	333.4***
	(0.670)	(0.597)	(0.757)	(1.104)	(9.459)
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 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) Total market payoff
Nudge	-0.997	0.512	1.804	0.447	-2.400
	(0.709)	(0.597)	(1.190)	(0.864)	(18.71)
Constant	0.702	-0.800*	-5.978***	2.471***	336.6***
	(0.527)	(0.480)	(1.100)	(0.599)	(12.30)
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 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) Total market payoff
Reputation	0.355	-0.232	2.369	-0.254	-7.200
	(0.865)	(0.787)	(1.598)	(0.974)	(19.10)
Constant	-0.657	-0.106	-6.947***	3.695***	341.4***
	(0.687)	(0.654)	(1.357)	(0.746)	(12.88)
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 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) Total market payoff
Reputation	-0.402	0.291	0.750	-1.828*	1.600
	(1.162)	(1.190)	(1.640)	(0.944)	(7.783)
Constant	2.620**	-2.863***	-7.837***	5.568***	327.8***
	(1.040)	(1.071)	(1.965)	(1.093)	(6.420)
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 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) Total market payoff
Nudge	-3.516	2.317	-0.0156	-1.234	11
	(3.390)	(2.596)	(3.401)	(0.995)	(8.458)
Constant	4.309*	-4.204**	-9.789**	5.523***	327.8***
	(2.227)	(1.964)	(4.792)	(1.217)	(6.420)
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 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) Total market payoff
Reputation+Nudge	-2.416*	1.849	2.480	-0.972	16*
	(1.313)	(1.267)	(1.932)	(0.934)	(8.266)
Constant	2.659**	-2.896***	-8.469***	5.795***	327.8***
	(1.048)	(1.078)	(2.099)	(1.242)	(6.420)
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 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) Total market payoff
Nudge	-1.664	1.362	1.477	0.778	14.40**
	(1.029)	(1.051)	(1.453)	(0.983)	(6.816)
Constant	1.850**	-2.174***	-7.149***	3.288***	329.4***
	(0.749)	(0.818)	(1.537)	(0.895)	(4.399)
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 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) Total market payoff
Reputation	-0.162	0.0389	2.480	0.152	5
	(1.542)	(1.645)	(1.932)	(0.993)	(7.578)
Constant	0.433	-1.238	-8.469***	3.846***	338.8***
	(1.233)	(1.361)	(2.099)	(0.782)	(5.506)
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 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

Appendix C: Procedures of finding the Pareto-efficient PPE

(Note: To simply 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 denoted as $w_{HL,M}$; $w_{q^h q^h,Cry}$ is denoted as $w_{HH,R}$; $w'_{q^h q^h,Cry}$ is denoted as $w'_{HH,R}$; $w''_{q^h q^h,Cry}$ 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):

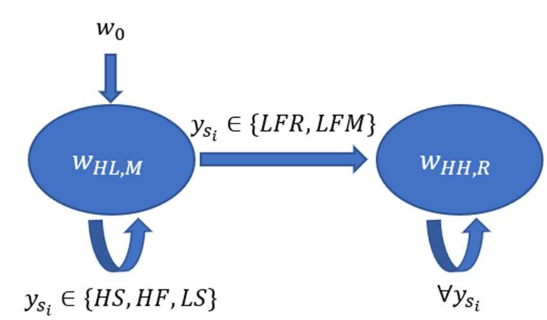

Figure C.1: Automaton for the "grim-trigger" strategy profile

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:

$$\tau(w,y) = \begin{cases} w_{HL,M} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \\ w_{HH,R} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{LFR, LFM\}\right) \text{ or } \left(w = w_{HH,R} \text{ and } y_{s_i} \in \{HS, HF, LS, LFR, LFM\}\right) \end{cases} \tag{51}$$

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 payoff in the state $w_{HL,M}$ in Period t:

$$V_b^t(w_{HL,M}) = (1-\delta)[h(\lambda v - p^h) + (1-h)(\lambda v - p^l)] + \delta[\psi^{t+1} V_b^{t+1}(w_{HL,M}) + (1-\psi^{t+1}) V_b^{t+1}(w_{HH,R})] \tag{52}$$

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 $w_{HH,R}$.[38]

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

$$\begin{aligned} g_b^t(w_{HL,M}, R) = (1-\delta)\left[h(\lambda v - p^h) + (1-h)\left(\lambda v - p^l + (1-\lambda)(\beta - \gamma)\right)\right] \\ +\delta[\psi^{t+1} V_b^{t+1}(w_{HL,M}) + (1-\psi^{t+1}) V_b^{t+1}(w_{HH,R})] \end{aligned} \tag{53}$$

We can easily see that $g_b^t(w_{HL,M}, R) > V_b^t(w_{HL,M})$, 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:

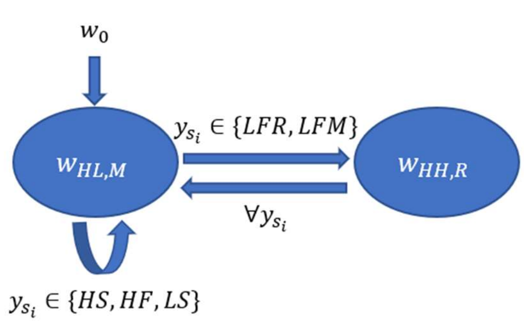

Figure C.2: Automaton for the "tit-for-tat" strategy profile

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

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:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } (w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\}) \text{ or } (w = w_{HH,R} \text{ and } y_{s_i} \in \{HS, HF, LS, LFR, LFM\}) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{LFR, LFM\} \end{cases} \quad (54)$$

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 payoff in the state $w_{HL,M}$, $V_b^t(w_{HL,M})$, and her average discounted payoff 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 (51) and (52) respectively.[39]

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):

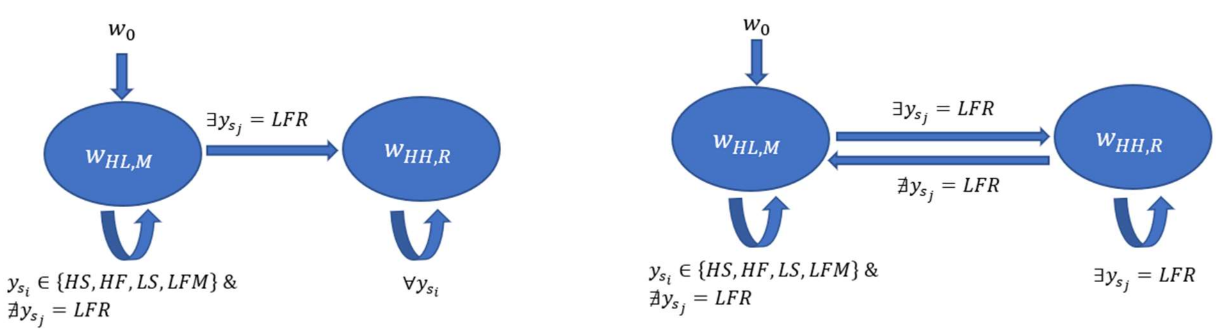

Figure C.3: Revised "grim-trigger" and "tit-for-tat" strategy profiles

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:

$$\tau(w, a) = \begin{cases} w_{HL,M} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS, LFM\} \text{ and } \nexists y_{s_j} = LFR \\ w_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w_{HH,R} \end{cases} \quad (55)$$

[39] 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 $g_b^t(w_{HL,M}, R) > V_b^t(w_{HL,M})$.

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:

$$\tau(w,a) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS, LFM\} \text{ and } \nexists y_{s_j} = LFR\right) \\ & \text{or} \left(w = w_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \\ w_{HH,R} & \text{if } \exists y_{s_j} = LFR \end{cases} \tag{56}$$

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 payoff in the state $w_{HL,M}$ is:

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta V_s(w_{HL,M}) \tag{57}$$

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

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

$$g_s(w_{HL,M}, LL) = (1-\delta)\pi^l + \delta V_s(w_{HL,M}) \tag{58}$$

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:

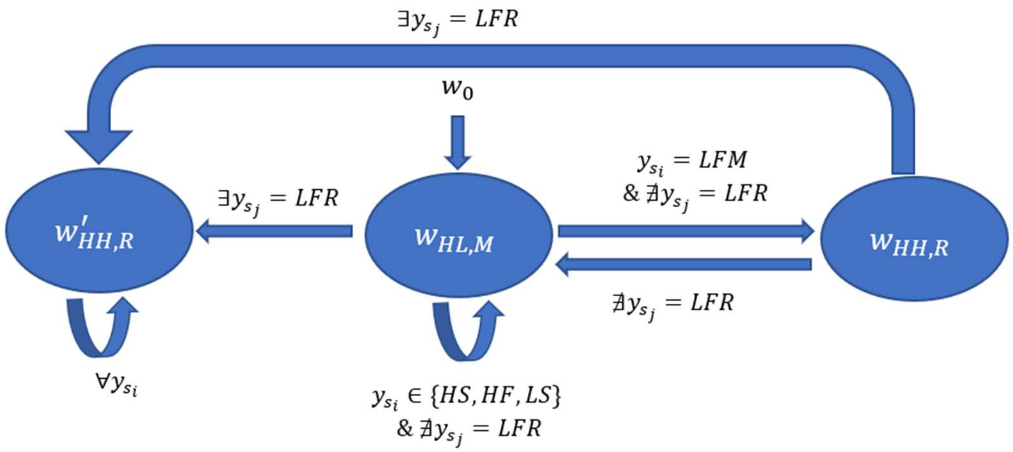

Figure C.4: A 1-period punishment hybrid strategy profile

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:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \text{ and } \nexists y_{s_j} = LFR\right) \\ & \text{or } \left(w = w_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} = LFM \text{ and } \nexists y_{s_j} = LFR \\ w'_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w'_{HH,R} \end{cases} \tag{59}$$

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 5 is not a PPE.

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

$$V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l] + \delta[(1-h)(1-\lambda)V_s(w_{HH,R}) + (1-(1-h)(1-\lambda))V_s(w_{HL,M})] \tag{60}$$

$$V_s(w_{HH,R}) = (1-\delta)\pi^h + \delta V_s(w_{HL,M}) \tag{61}$$

Plugging (61) into (60), I have:

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

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

$$\Rightarrow (1-\delta)[1+\delta(1-h)(1-\lambda)]V_s(w_{HL,M}) = (1-\delta)[h\pi^h + (1-h)\pi^l + \delta(1-h)(1-\lambda)\pi^h]$$
$$\Rightarrow V_s(w_{HL,M}) = \frac{h\pi^h + (1-h)\pi^l + \delta(1-h)(1-\lambda)\pi^h + \pi^h - \pi^h}{1+\delta(1-h)(1-\lambda)} = \pi^h + \frac{(1-h)\pi^h - (1-h)\pi^l}{1+\delta(1-h)(1-\lambda)}$$
$$= \pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)} \tag{62}$$

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

$$V_s(w_{HH,R}) = \pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)} \tag{63}$$

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

$$g_s(w_{HL,M}, LL) = (1-\delta)\pi^l + \delta\big[(1-(1-h)\lambda-(1-\lambda)h)V_s(w_{HH,R}) + ((1-h)\lambda+(1-\lambda)h)V_s(w_{HL,M})\big] \tag{64}$$

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

$$\begin{aligned}
&V_s(w_{HL,M}) - g_s(w_{HL,M}, LL)\\
&= (1-\delta)[h\pi^h + (1-h)\pi^l - \pi^l]\\
&+ \delta\big[V_s(w_{HH,R})\big((1-h)(1-\lambda) - (1-(1-h)\lambda-(1-\lambda)h)\big)\\
&+ V_s(w_{HL,M})(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)\big]\\
&= (1-\delta)(-h\Delta\pi)\\
&+ \delta\left[\left(\pi^h + \frac{\delta(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right)\big((1-h)(1-\lambda)+(1-h)\lambda+(1-\lambda)h-1\big)\right.\\
&\left.+\left(\pi^h + \frac{(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right)(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)\right]\\
&= (1-\delta)(-h\Delta\pi) + \delta\left[(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)\cdot\frac{(1-\delta)(1-h)\Delta\pi}{1+\delta(1-h)(1-\lambda)}\right]\\
&= (1-\delta)\Delta\pi\left[\frac{\delta(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h)(1-h)}{1+\delta(1-h)(1-\lambda)} - h\right]\\
&= (1-\delta)\Delta\pi\left[\frac{\delta(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h](1-h)}{1+\delta(1-h)(1-\lambda)} - \frac{h+h\delta(1-h)(1-\lambda)}{1+\delta(1-h)(1-\lambda)}\right]\\
&= (1-\delta)\Delta\pi\cdot\frac{\delta\big(1-(1-h)(1-\lambda)-(1-h)\lambda-(1-\lambda)h-h(1-\lambda)\big)(1-h)-h}{1+\delta(1-h)(1-\lambda)}\\
&= (1-\delta)\Delta\pi\cdot\frac{\delta h(1-h)(2\lambda-1)-h}{1+\delta(1-h)(1-\lambda)} = (1-\delta)\Delta\pi\cdot\frac{h[\delta(1-h)(2\lambda-1)-1]}{1+\delta(1-h)(1-\lambda)}
\end{aligned} \tag{65}$$

$$\left.\begin{aligned}\lambda\in(0.5,1)\Rightarrow 2\lambda-1\in(0,1)\\ \delta\in(0,1)\\ h\in(0,1)\end{aligned}\right\}\Rightarrow \delta(1-h)(2\lambda-1)-1<0 \tag{66}$$

From (65) and (66), 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:

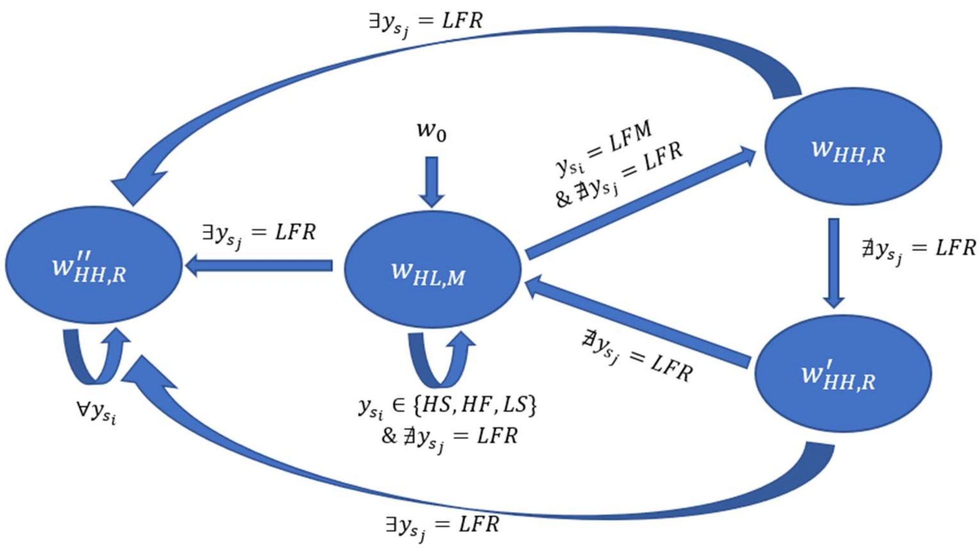

Figure C.5: A 2-period punishment hybrid strategy profile

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:

$$\tau(w, y) = \begin{cases} w_{HL,M} & \text{if } \left(w = w_{HL,M} \text{ and } y_{s_i} \in \{HS, HF, LS\} \text{ and } \nexists y_{s_j} = LFR\right) \\ & \quad \text{or } \left(w = w'_{HH,R} \text{ and } \nexists y_{s_j} = LFR\right) \\ w_{HH,R} & \text{if } w = w_{HL,M} \text{ and } y_{s_i} = LFM \text{ and } \nexists y_{s_j} = LFR \\ w'_{HH,R} & \text{if } w = w'_{HH,R} \text{ and } \nexists y_{s_j} = LFR \\ w''_{HH,R} & \text{if } \exists y_{s_j} = LFR \text{ or } w = w''_{HH,R} \end{cases} \tag{67}$$

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 6 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 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.