Job Market Signaling: An Experimental Study of Education Degree as an Imperfect Signal

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Abstract

Inspired by the phenomenon of dropouts, this paper introduces the risk of dropout into Spence's job market signaling model to explain the wage premium associated with academic degrees. I look at a labor market where the workers can pursue a degree with some cost, but may fail to meet the degree requirements and drop out involuntarily without the degree. Within this framework and assuming the dropout risk is higher for low-ability workers, I first relax the requirement on cost-difference in order to induce signaling behavior and explain the wage diffrential. Second, assuming workers have different risk attitudes, I propose a "partially separating equilibrium" in which the self-selection of workers into an education program depends both on their abilities and on their risk attitudes. Using lab experiments, I test these theoretical predictions with an focus on the effectiveness of Cho-Kreps intuitive criterion in equilibrium selection, and also elicit subjects' risk preferences to explain their strategies in the signaling games. Data show that separation in workers' educational choices is less complete when the pooling equilibrium cannot be refined by the criterion and when workers in the market are more risk averse.

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I. INTRODUCTION AND LITERATURE REVIEW

In US labor markets, there has been persistent evidence of wage premiums associated with having a higher academic degree between otherwise similar workers.[1] Signaling has been a popular explanation of this phenomenon: if workers with higher abilities self-select to pursue more advanced degrees, then a higher degree may be perceived as a signal of greater innate ability, and can result in the widely observed wage premium that cannot be explained by other factors, such as years of schooling or other observable attributes of the workers. Dating back to the seminal work "Job Market Signaling"(Spence (1973)), this self-fulfilling signaling process relies on the assumption that education cost is inversely related to ability. However, when we look at postsecondary education programs, it is not clear whether there is such a strong inverse relationship between the education costs and students' abilities. On the other hand, it is not uncommon to see students fail to meet the degree requirements after investing the costs, and drop out of the program involuntarily[2] – a risk of education investments that could also trigger the signaling process, even when the classical assumption proposed by Spence (1973) does not hold.

This paper extends the signaling literature by exploring how this dropout risk can trigger the self-selection process among workers, and result in a degree wage premium when, ceteris paribus, a worker with lower ability is at higher risk of involuntarily dropping out[3]. Specifically, I define the education cost as tuitions, expenses and forgone earnings in pursuit of a degree,[4] and the dropout risk as the likelihood of not earning the degree after enduring the costs.[5] In making this differentiation, I refrain from the risk neutral assumption and discuss how the workers' risk attitudes can

[1]Early evidence includes Hungerford and Solon (1987), Belman and Heywood (1991), John (1994), Hungerford and Solon (1987) and Jaeger and Page (1996). Using 1990 CPS data, Park (1999) finds that, among the individuals who have the same years of schooling, there are significant earning gains of 9, 11 and 21% from obtaining a high-school diploma, an associate's degree, and a bachelor's degree, respectively.

[2]In this paper, I only consider dropouts due to the inability of meeting degree requirements, and exclude dropouts due to changes of health/financial situations or of personal preferences for education.

[3]In Light and Strayer (2000), the authors use the Armed Forces Qualification Test (AFQT) score as a measure of ability, and ranked the responders to National Longitudinal Survey of Youth between 1979 and 1993 into four quartiles based on their AFQT scores. Using the subsample of 2635 responders who attended four-year college, they find the average completion rate increases as the AFQT score increases. Moreover, the completion rate more than doubles from the lowest AFQT quartile to the highest quartile.

[4]The education cost as defined in Spence (1973) includes financial costs, such as tuitions and living expenses, and disutility from effort, but fails to account for the opportunity cost such as foregone earnings. The exclusion of effort cost is mainly due to the difficulty of measuring it. On the other hand, even if we do consider disutility from effort, it may not differ much among students with different abilities in more advanced degree programs, considering these programs typically have challenging requirements that all students may need to study at the *same*, full effort level, regardless of their ability levels.

[5]For simplicity, I assume workers know both education costs and the *ex-ante* probability of dropout before deciding whether to pursue an academic degree.

affect the equilibrium in the labor market. In addition, with education cost defined to include the forgone earnings, there might not be much of a difference in it between workers with different abilities.[6] In this case, the inverse relationship between ability and dropout risk may become necessary in triggering the self-selection process among workers, and in explaining the observed degree wage premium.

In this paper, I first formalize the idea in a theoretical framework and then test the predictions with laboratory experiments. In the theoretical section, I look at a simplified scenario in which there are two types of workers in the labor market – those with high and those with low abilities. The workers need to decide whether to pursue an academic degree at some cost; to focus on the signaling role of education, I assume that pursuing the degree does not improve ability or productivity. After incurring the cost, there is a risk that workers fail the degree requirements and drop out without the degree, and such risk is greater for workers of the low-ability type. I find that even when the costs are the same for both types, if dropout risks are sufficiently different, the market may still have a separating equilibrium[7] and it may be the only Perfect Bayesian Nash Equilibrium that satisfies refinement based on the Cho-Kreps Intuitive Criterion[8]. Data from the lab experiments generally support the predictions from the model, and also suggest that subjects learn to play the game throughout the many market periods.

Considering the presence of the dropout risk, the discussion on risk attitudes become quite relevant and necessary. Therefore, another focus of this paper, both in the theoretical discussion and in the experimental design, is to investigate the effects of workers' risk attitudes on the equilibrium of the labor market. From the theoretical discussion, I find that the more risk-averse a worker is, the less likely he or she will pursue the degree due to the wage variations associated with the possibility of dropout. Further, when workers have different risk attitudes, there is also a selection effect on risk attitudes in their educational decisions. Under some conditions, the market may not have a complete separating equilibrium, but only a partially separating equilibrium, in which the most risk-averse high-type workers choose not to pursue the degree. This effect is in line with the

[6] Arguably, the less able can spend more years in the degree program and, therefore, endure greater costs; however, most programs post an expiration date on the credits earned by the students, so there is a limit to how much the costs can increase. Another argument is that outstanding students might be able to acquire scholarships and lower their cost, but the earnings they have forgone may be greater too.

[7] In a separating equilibrium, the high type pursues the degree, while the low type does not; recognizing this, employers offer higher wages to degree holders in the labor market. In a pooling equilibrium, neither the high type nor the low type pursues the degree, and employers offer the same wages to them since they cannot distinguish one type from the other.

[8] Cho and Kreps (1987) came up with the "Intuitive Criterion" to rule out the equilibrium supported by unreasonable out-of-equilibrium beliefs – in the current context, the pooling equilibrium. Details of this criterion will be discussed in Section 2.

commonly observed incomplete separation in the experimental literature on signaling games. In light of the theoretical findings, I include binary lottery tasks to elicit subjects' risk preferences in the experiments, and use them as controls in explaining their strategies in the signaling games. The data from the experiments partly confirm the theoretical predictions.

Although developed in the context of job market signaling, this paper contributes to the literature on general signaling games by introducing *type-dependent noise* to relax the classical assumption underlying signaling phenomenon, and by discussing the effects of agents' *heterogeneous risk attitudes* in equilibrium strategies. Matthews and Mirman (1983) were the first to look at stochastic signaling games by introducing demand shocks to the incumbent's price choice in the entry limit pricing game.[9] Landeras and Villarreal (2005) present a screening model with performance noise to the educational credentials and conclude that over-education is made worse by the noise in students' credentials. In more recent works, de Haan et al. (2011) and Jeitschko and Normann (2012) introduce noises to general signaling games with different focuses: the former on the effects of different noise levels and the latter on prior distributions of sender type. However, these studies commonly assume the same distribution of noise across sender types, so their models still rely on the difference in signaling costs to induce signaling behavior.

In contrast to those earlier models, the current model allows the noise distributions to differ across sender types, which relaxes the requirement on the cost-difference to induce signaling behavior. In the current setup, the type of senders who are more desirable to the receivers (the high ability workers) have greater control over the signal generating process (better chances of passing the degree requirements) than the less desirable type. To highlight this point, I focus the theoretical discusssion and experimental design on how the type-dependent noises can trigger signaling behavior, when the signaling costs are the same across different sender types. In a similar vein, Regev (2012) introduces a test for which the likelihood of passing is higher for high-ability workers. However, in their setup, all workers can take the test regardless of their educational backgrounds, which essentially reduces the signal cost to zero. Therefore, their study arrives at the completely different prediction that a separating equilibrium does not exist. As I will argue in Section 2, the existence of a positive signaling cost, albeit the same across different types, is essential for a separating equilibrium to exist in this market.

[9]Based on their work, Carlsson and Dasgupta (1997) propose the "noise-proof" criterion as the equilibrium selection tool in deterministic signaling games.

This paper also contributes to the experimental literature on signaling games, by testing an alternative signaling mechanism and investigating the effects of subjects' risk attitudes in this mechanism. Lab experiments have been a powerful tool to shed light on the signaling phenomenon, since they allow researchers to control or observe all relevant parameters that are either not possible or hard to control or observe with field data. Since the 1980s, deterministic signaling models have been tested using lab experiments in both market environments (Miller and Plott (1985), Cadsby et al. (1990, 1998), Cooper et al. (1997b), Cooper and Kagel (2003), Posey and Yavas (2007), and Kübler et al. (2008)) and non-market environments (Brandts and Holt (1992), Banks et al. (1994) and Potters and van Winden (1996)). The commonly investigated question is: when the parameters are within the experimenter's control, do subjects behave as the theory predicts? These studies commonly find that subjects behave generally consistently with the equilibrium predictions; however, the extent to which observations are consistent with theoretical predictions is never 100%. They also find that subjects sometimes, but not always, play the more refined equilibrium when the game has multiple equilibria, depending on the complexity of games and the design of experiments. [10]

Jeitschko and Normann (2012) and de Haan et al. (2011) are the first to test *stochastic signaling models* using lab experiments. In both studies, different types have different signal costs but share the same distribution over the signal noise – the same feature that differentiates their studies from the current paper in the theoretical setup of signaling models. In addition, the experiments in both papers do not consider subjects' risk preferences when examining their decisions in the signaling games, despite of the stochastic nature of the games. Their data support the comparative statics well, but generally do not converge completely to the theoretical equilibrium predictions derived under assumptions of risk neutrality. However, their findings that the high type chooses too little effort (Jeitschko and Normann (2012), pp.49) and that relative frequencies of pooling increases with noise level (de Haan et al. (2011), pp.412) are somewhat in line with risk averse behavior among sellers.

To investigate whether risk aversion can contribute to explaining the commonly-observed incomplete separation, I include an additional stage to elicit subjects' attitudes as a control in investigating their strategic decisions in the signaling games. In this second stage, subjects choose a preferred lottery from series of lottery pairs. In each lottery pair, there is a safer option and a riskier

[10] The intuitive criterion is a popular refinement measure tested in these experiments. Brandts and Holt (1992, 1993) and Cooper and Kagel (2003), Cooper et al. (1997a) find evidence indicating subject behavior may contradict the Intuitive Criterion and follow history-dependent learning processes when the payoff structures make it harder for them to apply this forward-induction-based reasoning.

option; by observing their choices, we can infer whether they are more or less risk averse than each other.[11] The findings are somewhat, but not completely, consistent with the theoretical predictions on the effects of risk attitudes. That is, more risk averse workers are less likely to pursue the degree; the observed incomplete separating can be explained, in some cases and to a certain degree, by the differences in agents' risk attitudes.

In Section 2, I develop the model to accommodate both heterogeneous costs and heterogeneous noises between the two types, and I discuss the implications of homogeneous costs as a special case. In Section 3, I describe the experiment design and procedures;[12] to focus sharply on the role of dropout risk in signaling behavior, I have kept signal costs the same while imposing different dropouts risks on both types in the experiments. Section 4 presents the data and results, and Section 5 concludes.

II. Model

Suppose that in a labor market, we have two types of workers, either high-ability or low-ability, and the proportion of the low ability type is μ. Assume that different abilities lead to different productive efficiencies when workers are hired: the more able workers will have higher productivity θ_h, while the less able workers will have lower productivity θ_l, and we have $\theta_h > \theta_l$. Workers can choose to pursue an academic degree at a cost of c; assume that higher ability leads to a lower cost of the degree, so we have $0 < c_h < c_l$. This is the standard assumpiton of an inverse relationship between education costs and abilities, and as I will show later, it drives signaling behavior in the deterministic signaling models or stochastic signaling model with homogeneous dropout risks. Further, I will relax this assumption, and discuss the existence of an separating equilibrium even with $0 < c = c_h = c_l$.

If a worker decides to incur the cost and pursue the degree, with probability λ, she will fail to meet the degree requirements and have to drop out without earning the degree; assume that higher ability also leads to a lower risk of dropout, so we have $0 \leq \lambda_h < \lambda_l$. Denote the high type's choice as $e_h \in \{0,1\}$ and the low type's as $e_l \in \{0,1\}$, where 1 means pursuing and 0 means not pursuing

[11] The "binary lottery task" is one of the most popular methods in eliciting subjects' risk attitudes in the experimental economics literature. The simplicity of the task allows a relatively more robust inference on subjects' risk attitudes, compared to other decision tasks that involve complicated joint assumptions on subjects' decision rules.

[12] The experiment procedures of the current paper are similar to those in Kübler et al. (2008); their experiments can be seen as a parametrization of the current model with different education costs and no dropout risk.

the degree. Denote a worker's degree status as $D \in \{0,1\}$, where 1 means a worker has the degree and 0 means not; then, we have

$$\lambda_h = \text{Prob}\{D = 0 | e_h = 1\}, \quad \lambda_l = \text{Prob}\{D = 0 | e_l = 1\}. \tag{1}$$

Assume that employers are competing to hire workers in a perfectly comepitive market– if they can directly observe a worker's type at the time of hiring, they will offer a wage that is equal to her productivity.[13] However, ability is not directly observable at the time of hiring, so employers will offer the worker a wage that they *believe* to be consistent with her productivity, based on her degree status. Assume that employers can observe a worker's degree status but not her education choice, that is, they cannot *credibly* differentiate the dropouts from those who have decided not to pursue the degree. Once hired, a worker's type will eventually be revealed in production, and employers can update their beliefs for the next round of hiring.[14] Suppose that employers believe that a worker *without* the degree has a likelihood μ_0 of being the low type, and a worker *with* the degree has a likelihood μ_1 of being the low type; that is,

$$\mu_0 = \text{Prob}\{\theta = \theta_l | D = 0\}, \quad \mu_1 = \text{Prob}\{\theta = \theta_l | D = 1\}. \tag{2}$$

2.1 Risk Neutral Agents

Assume that education does not improve workers' productivity[15] and that all agents are risk-neutral. The strategic decisions in this model can be characterized as follows:

i) Based on prevalent wage offers, a worker will maximize her expected payoff (defined as wage net of education cost), and a type i worker will choose to pursue the degree only when this leads to

[13] If employers have more bargaining power and workers are competing for jobs, then the equilibrium wage will be driven down to the reservation wage regardless of a worker's productivity. The assumption that employers will offer wages equal to a worker's productivity comes from the neoclassical profit-maximization problem of competitive firms. However, this assumption is not crucial to the current model. We can think of θ_h and θ_l as how much a firm is willing to pay to hire the high type and the low type, and that firms are willing to pay more to hire a worker with higher ability.

[14] An alternative way to credibly reveal a worker's type is to strike a long-term contract with the same initial wages, and increase the wage of the high type based on performance later. However, under the assumption that employers are competing for workers, a high-type worker is unlikely to accept such a contract from one employer, when another is willing to offer what she deserves from the beginning of the contract.

[15] The purpose of this assumption is to keep the discussion sharply focused on the signaling process, and it should not be taken as a complete denial in the productivity-improving function of education. Note that the framework in this section allows the incorporation of productivity-improving function, which will shift the wage offer $w(1)$ up by the increment in productivity.

a higher expected payoff:

$$w(0) < (1-\lambda_t) \cdot (w(1) - c_t) + \lambda_t \cdot (w(0) - c_t),\ t \in \{h, l\}. \tag{3}$$

ii) Based on post-hiring verification, employers' beliefs μ_0 and μ_1 should be updated using Bayes' rule whenever possible.[16] Employers will offer a wage that is equal to a worker's expected productivity, given her degree status:

$$w(D) = \begin{cases} (1-\mu_0)\ \theta_h + \mu_0\ \theta_l, & D = 0 \\ \\ (1-\mu_1)\ \theta_h + \mu_1\ \theta_l, & D = 1. \end{cases} \tag{4}$$

The market is in Perfect Bayesian Equilibrium if workers' educational decisions and employers' wage offers sustain each other. There are potentially three pure-strategy equilibria: both types choose not to pursue a degree ($e_h = e_l = 0$); the high type pursues, while the low type does not ($e_h = 1, e_l = 0$); and both workers choose to pursue the degree ($e_h = e_l = 1$). For the sake of brevity, I will refer to the three cases as "pooling not to pursue", "separating" and "pooling to pursue" hereafter. In Appendix C, I discuss the decision processes outlined in i) and ii) for each case. Here, I present the equilibrium predictions in the first proposition.

Proposition 1 Pooling not to pursue is always an equilibrium of this market, while separating is an equilibrium if and only if the education costs and dropout risks satisfy

$$\frac{c_h}{1-\lambda_h} \leq \frac{\mu}{\mu + \lambda_h(1-\mu)}(\theta_h - \theta_l) \leq \frac{c_l}{1-\lambda_l}. \tag{5}$$

When the above condition is satisfied, the inefficient case in which both workers pursue the degree is *not* an equilibrium.

Although pooling not to pursue is always a Perfect Bayesian Equilibrium, it is supported by employers' out-of-equilibrium beliefs that associate a degree holder with the low type with some probability. Such beliefs are particularly counterintuitive when the low type's cost or dropout risk is so high that, in expectation, they would not benefit from pursuing the degree, even when the

[16] Beliefs associated with out-of-equilibrium strategies are not restricted by the Perfect Bayesian Equilibrium solution, as employers cannot frequently observe such behavior to verify the type, but refinement on out-of-equilibrium beliefs will be applied later.

employers offer the highest possible wage, θ_h, to degree holders. To refine multiple equiliria in signaling games, Cho and Kreps (1987) came up with the "Intuitive Criterion" to rule out the equilibrium supported by unintuitive out-of-equilibrium beliefs. In the current context, the criterion requires that employers do not associate degree holders with the low type, when it is not profitable for the low type to deviate and pursue the degree, while it might be for the high type. In Appendix C, I derive the conditions under which we can refine the pooling equilibrium based on the Intuitive Criterion, and the following proposition presents my conclusion.

Proposition 2 Pooling not to pursue can be refined by the Cho-Kreps intuitive criterion if the costs and dropout risks satisfy

$$\frac{c_h}{1-\lambda_h} < \mu(\theta_h - \theta_l) < \frac{c_l}{1-\lambda_l}. \tag{6}$$

Combing this condition with the condition for the existence of a separating equilibrium in (5) , separating will be the *only* intuitive Perfect Bayesian Equilibrium when

$$\frac{c_h}{1-\lambda_h} < \mu(\theta_h - \theta_l) < \frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h - \theta_l) < \frac{c_l}{1-\lambda_l}. \tag{7}$$

Fixing θ_h, θ_l and μ, several interesting cases arise if we change the assumptions on education cost and dropout risk. If we eliminate the difference in education costs between the two types such that $c_h = c_l = c > 0$, then condition (7) adapts to

$$1-\lambda_h > \frac{1}{\mu}\cdot\frac{c}{\theta_h-\theta_l} > \frac{\mu+\lambda_h(1-\mu)}{\mu}\cdot\frac{c}{\theta_h-\theta_l} \geq 1-\lambda_l. \tag{8}$$

That is, in absence of an inverse relationship between education costs and abilities, as long as the dropout risk is sufficiently low for the high type and sufficiently high for the low type, a separating equlibrium can exist. The high ability workers will pursue the degree while the low type will not; consequently, employers can use the degree as a signal of high ability. Note that education costs should always be positive (non zero); otherwise, the low type will always pursue the degree, even when their dropout risk is very high.

Corollary 1 When education costs are the same for both types of workers $c_h = c_l = c > 0$, separating is the only intuitive Perfect Bayesian Equilibrium when the dropout risk is sufficiently low for the high type and sufficiently high for the low type:

$$1-\lambda_h > \frac{1}{\mu}\cdot\frac{c}{\theta_h-\theta_l} > \frac{\mu+\lambda_h(1-\mu)}{\mu}\cdot\frac{c}{\theta_h-\theta_l} \geq 1-\lambda_l. \tag{9}$$

As the second case, if we eliminate dropout risk from the model such that $\lambda_h = \lambda_l = 0$, the model reduces to the standard, deterministic signaling model, and condition (7) adapts to

$$c_h < \mu(\theta_h-\theta_l) < \theta_h-\theta_l \leq c_l. \tag{10}$$

In contrast to the original condition (7), without dropout risks and other parameters constant, the cost for the low types c_l will have to be higher to deter them from pursuing the degree since $\theta_h-\theta_l > \frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h-\theta_l)(1-\lambda_l)$, while the cost for the high types will not need to be that low to encourage them to pursue the degree since $\frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h-\theta_l)(1-\lambda_h) < \theta_h-\theta_l$. Further, in order to apply the Cho-Kreps Intuitive criterion to rule out the pooling equilibrium, the difference between c_l and c_h has to be greater than $(1-\mu)(\theta_h-\theta_l)$.

Finally, if we assume there are dropout risks but they are the same between the two types, $\lambda_h = \lambda_l = \lambda > 0$, the model becomes the stochastic model with homogeneous dropout risks, and condition (7) adapts to

$$c_h < \mu(1-\lambda)(\theta_h-\theta_l) < \frac{\mu}{\mu+\lambda(1-\mu)}(1-\lambda)(\theta_h-\theta_l) \leq c_l. \tag{11}$$

From this condition, it is clear that when there are dropout risks but when they are the same for the two types, the education costs need to be different in order for separating equilibrium to exist. However, compared to the condition (10) without dropout risk, we observe that the cost for high type does not need to be as high, while the cost for the low type needs to be lower. As an additional requirement, in order for separating to be the unique equilibrium prediction subject to the Cho-Kreps Intuitive Criterion, the difference between c_h and c_l must be greater than $(\frac{\mu}{\mu+\lambda(1-\mu)}-\mu)(1-\lambda)(\theta_h-\theta_l)$.

2.2 Effects of Workers' Risk Attitude

The discussion up to this point has assumed that agents in the labor market are risk-neutral; however, the presence of dropout risk in pursuit of an academic degree makes the discussion of workers' risk attitudes quite relevant.[17] Assume workers maximize their expected utilities and that w and c are perfect substitutes in workers' utility function, $u(w,c) = u(w-c)$. In separating equilibrium, workers' incentive constraints in terms of expected utility are:

$$(1-\lambda_h)\cdot\mathbf{u}\big(w(1)-c_h\big)+\lambda_h\cdot\mathbf{u}\big(w(0)-c_h\big)\geq\mathbf{u}\big(w(0)\big) \tag{12}$$

$$(1-\lambda_l)\cdot\mathbf{u}\big(w(1)-c_l\big)+\lambda_l\cdot\mathbf{u}\big(w(0)-c_l\big)\leq\mathbf{u}\big(w(0)\big) \tag{13}$$

Assume that the workers are risk-averse, $\mathbf{u}'(\ )>0$ and $\mathbf{u}''(\ )<0$; then, for $t=h,l$ we have

$$(1-\lambda_t)\mathbf{u}\big(w(1)-c_t\big)+\lambda_t\mathbf{u}\big(w(0)-c_t\big)<\mathbf{u}\big((1-\lambda_t)(w(1)-c_t)+\lambda_t(w(0)-c_t)\big) \tag{14}$$

$$=\mathbf{u}\big((1-\lambda_t)w(1)+\lambda_t w(0)-c_t\big) \tag{15}$$

That is, more risk averse workers' have lower expected utilities of pursuing the degree, due to the possibility of dropout and the wage variability.

Now compare the two incentive constraints (12) and (13) with their counterparts under the risk-neutral assumption (C.6) and (C.7) in Appendix Proof. The incentive constraint for the low type under risk averse assumption (13) is less stringent than that under risk neutral assumption (C.7):

Lemma 3 If $(1-\lambda_l)w(1)+\lambda_l w(0)-c_l\leq w(0)$, then $(1-\lambda_l)\mathbf{u}\big(w(1)-c_l\big)+\lambda_l\mathbf{u}\big(w(0)-c_l\big)<\mathbf{u}\big((1-\lambda_l)w(1)+\lambda_h w(0)-c_l\big)\leq\mathbf{u}\big(w(0)\big)$

The lemma states that, when the low-type workers are risk-averse, the education cost or dropout risk does not need to be as high as in the risk-neutral case in order to deter them from pursuing the academic degree and to induce separation. However, the incentive constraint for the high type under risk averse assumption (12) is more stringent than that under risk neutral assumption (C.6):

[17] Hiring a worker, in this model, is essentially buying a lottery with two outcomes: θ_h and θ_l; if we refrain from the risk-neutral employer assumption, the wage offer will be the certainty equivalents rather than the expected values of the lotteries, conditional on employers' beliefs. I will leave the effect of the employer's risk attitudes to be empirically evaluated in the experiment results section, while focus on the risk attitudes of workers in this section.

Lemma 4 If $(1-\lambda_h)\mathbf{u}\big(w(1)-c_h\big)+\lambda_h\mathbf{u}\big(w(0)-c_h\big) \geq \mathbf{u}\big(w(0)\big)$, then $\mathbf{u}\big((1-\lambda_h)w(1)+\lambda_h w(0)-c_h\big) > (1-\lambda_h)\mathbf{u}\big(w(1)-c_h\big)+\lambda_h\mathbf{u}\big(w(0)-c_h\big) \geq \mathbf{u}\big(w(0)\big)$; that is, $(1-\lambda_h)w(1)+\lambda_h w(0)-c_h > w(0)$.

Risk aversion among high type requires the education cost or the dropout risk to be lower than in the risk-neutral case, in order to encourage the high type to pursue the degree.[18] Therefore, risk aversion moves the boundaries of the parameter regions in which the separating equilibrium exists, while the overall structure of the analysis stays the same.

The discussion of workers' risk attitudes thus far rests on an implicit assumption that all workers have the same risk preferences. When workers have heterogeneous risk attitudes, we may have incomplete separating in terms of workers' educational choices. Assume workers can be characterized by Constant Relative Risk Aversion (CRRA) utility function $u^i(x) = \frac{x^{(1-r^i)}}{1-r^i}$, and a worker with higher CRRA coefficient r^i is more risk averse. Assume that the cumulative distribution of r^i is $F_h(r)$ among high-type workers and $F_l(r)$ among low-type workers.

Assume the distribution of risk attitudes are the same among the high and low type workers, that is, $F_h(r) = F_l(r) = F(r)$ for all r. Worker i will only pursue the degree if it gives her higher expected utility given her type t

$$(1-\lambda_t)\cdot \mathbf{u^i}\big(w(1)-c_t\big)+\lambda_t \cdot \mathbf{u^i}\big(w(0)-c_t\big) > \mathbf{u^i}\big(w(0)\big) \quad t = h, l \tag{16}$$

For some wage schedule $w(1) > w(0)$, assume that (16) takes the equal sign at r_h for the high type workers, and at r_l for the low type workers. Note worker i's expected utility of pursuing the degree is the left hand side of (16), which decreases as she becomes more risk averse with a higher r^i. Therefore, high type workers with $r^i < r_h$ and low type workers with $r^i < r_l$ will pursue the degree.

Modify the definition of e_h and e_l as the percentage of workers who will pursue the degree, among the high and low type, respectively:

$$e_h = F(r_h), \ e_l = F(r_l). \tag{17}$$

Note given $c_h < c_l$ and $\lambda_h < \lambda_l$, we should have $r_h > r_l$ as long as $w(1) > w(0)$. That is, we will have $e_h > e_l$ if $w(1) > w(0)$. Given e_h and e_l, risk neutral employers will update their beliefs and

[18] Meanwhile, if we are looking at risk-loving workers, the conclusions will be reversed for these two types, respectively.

offer wages as below [19]

$$\mu_0 = \frac{\mu(1-e_l)+\mu e_l\lambda_l}{\mu(1-e_l)+\mu e_l\lambda_l+(1-\mu)(1-e_h)+(1-\mu)e_h\lambda_h} \tag{18}$$

$$\mu_1 = \frac{\mu e_l(1-\lambda_l)}{\mu e_l(1-\lambda_l)+(1-\mu)e_h(1-\lambda_h)} \tag{19}$$

$$w(D) = \begin{cases} (1-\mu_0)\ \theta_h+\mu_0\ \theta_l, & D=0 \\ (1-\mu_1)\ \theta_h+\mu_1\ \theta_l, & D=1. \end{cases} \tag{20}$$

The market will be in equilibrium when workers choices in (17), given the distribution of their risk attitudes, and employers wage offers in (20), given their updated beliefs, sustain each other.

Depending on the distribution of workers' risk preferences, the market may or may not have a complete separating equilibrium, in the sense that all high-type workers choose to pursue the degree and low-type workers choose not to. To see this, start with productivity distribution $(\theta_h, \theta_l, \mu)$, education costs (c_h, c_l) and dropout risks (λ_h, λ_l) that satisfy condition (5). That is, we consider a vector of parameters that, if all workers are risk neutral, a pure-strategy separating equilibrium exists. For ease of discussion, I provide the characterization of the pure-strategy separating equilibrium with risk neutral workers as below (original derivation in Appendix Proof):

$$e_h^{\text{Pure}} = 1 \tag{21}$$

$$e_l^{\text{Pure}} = 0 \tag{22}$$

$$\mu_0^{\text{Pure}} = \frac{\mu}{\mu+\lambda_h(1-\mu)} \tag{23}$$

$$\mu_1^{\text{Pure}} = 0 \tag{24}$$

$$w^{\text{Pure}}(0) = \frac{\lambda_h(1-\mu)}{\mu+\lambda_h(1-\mu)}\cdot\theta_h + \frac{\mu}{\mu+\lambda_h(1-\mu)}\cdot\theta_l \tag{25}$$

$$w^{\text{Pure}}(1) = \theta_h \tag{26}$$

With the same parameters and when workers have heterogeneous risk attitudes, the compelete separating strategy profile as described in (21)-(26) may no longer be an equilibrium, depending on the distribution of workers' risk attitudes. To see this, first we find the threshold values r_h^{Pure} and r_l^{Pure} where high- and low-type workers are indifferent between pursuing and not pursuing the degree, given $w^{\text{Pure}}(0)$ and $w^{\text{Pure}}(1)$ as specified in (25) and (26), by solving the equation below for high

[19] An implicit assumption is that each worker's risk attitudes are not observable to employers. However, assume the distribution of the risk attitudes among high and low type workers is common knowledge.

and low type workers:

$$(1-\lambda_t)\cdot \mathbf{u^i}\left(w^{\text{Pure}}(1)-c_t\right)+\lambda_t\cdot \mathbf{u^i}\left(w^{\text{Pure}}(0)-c_t\right)=\mathbf{u^i}\left(w^{\text{Pure}}(0)\right) \quad t=h,l \tag{27}$$

Based on these threshold values, if the cumulative distribution $F(r)$ is such that $F(r_h^{\text{Pure}})=1$ and $F(r_l^{\text{Pure}})=0$, then all high-type workers pursue the degree and no low-type workers does, employers belief will remain the same as in (23) and (24), which will lead to the same wage offers in (25) and (26). The complete separating equilibrium as specified in (21)-(26) is now still a Perfect Bayesian equilibrium of the market, even with non-risk neutral workers.

However, if the cumulative distribution $F(r)$ is such that $F(r_h^{\text{Pure}})<1$ or $F(r_l^{\text{Pure}})>0$, then the market can not have a complete pure-separating equilibrium as with risk neutral workers. Starting with the wages in the complete pure-strategy separating equilibrium in (25) and (26), now we have $e_h=F(r_h^{\text{Pure}})<1$ and $e_l=F(r_l^{\text{Pure}})>0$, that is, the most risk-averse high-type workers with $r^i>r_h^{\text{Pure}}$ will not pursue the degree, while the least risk-averse low-type workers with $r^i<r_l^{\text{Pure}}$ will pursue the degree. This deviation in workers' decisions from (21) and (22) now breaks the equilibrium, and we may only have a paritally separating equilibrium with $1>e_h>e_l>0$.

To illustrate, consider an example with the following parameters:

$$\theta_h=25,\theta_l=10,\mu=0.5,c_h=c_l=5,\lambda_h=0.4,\lambda_l=0.8 \tag{28}$$

First, a pure-strategy separating equilibrium exists when workers are risk neutral under these parameters, and we have

$$e_h^{\text{Pure}}=1,\ e_l^{\text{Pure}}=0,\ \mu_0^{\text{Pure}}=0.71,\ \mu_1^{\text{Pure}}=0,\ w^{\text{Pure}}(0)=14.29,\ w^{\text{Pure}}(1)=25. \tag{29}$$

Based on $w^{\text{Pure}}(0)=14.29$ and $w^{\text{Pure}}(1)=25$, we have $r_h^{\text{Pure}}=1.4$ and $r_l^{\text{Pure}}=-3.4$ by solving (27), which correspond to very high levels of risk aversion and risk loving. If all workers' CRRA coefficients are within the interval $(-3.4,1.4)$, then we have $e_h=F(1.4)=1$ and $e_l=F(-3.4)=0$ given $w^{\text{Pure}}(0)=14.29$ and $w^{\text{Pure}}(1)=25$, which coincides with workers strategies under risk neutral assumption, and the complete separating strategy as described by (29) is still an equilibrium even with heterogeneous, non-risk neutral workers.

However, with the same market parameters, a partial separating equilibrium may also exists as described below

$$e_h^{\text{Partial}} = F(0.48) = 0.5,\ e_l^{\text{Partial}} = 0, \tag{30}$$

$$\mu_0^{\text{Partial}} = 0.61,\ \mu_1^{\text{Partial}} = 0,\ w^{\text{Partial}}(0) = 16.2,\ w^{\text{Partial}}(1) = 25. \tag{31}$$

That is, if the median of the distribution on workers' CRRA coefficients is 0.48, then we'll have a partial separating equilibrium in which only one half of high type workers with $r^i \leq 0.48$ pursue the degree, and none of the low-type workers does. Based on workers' decisions, employers update their beliefs according to (18) and (19), and we have $\mu_0^{\text{Partial}} = 0.61, \mu_1^{\text{Partial}} = 0$. Based on these beliefs, risk neutral employers offer wages $w^{\text{Partial}}(0) = 16.2$ and $w^{\text{Partial}}(1) = 25$. Now check that these wage offers are consistent with workers decisions according to (16):[20]

$$(1-0.4)\frac{(25-5)^{1-0.48}}{1-0.48} + 0.4\frac{(16.2-5)^{1-0.48}}{1-0.48} = \frac{16.2^{1-0.48}}{1-0.48} \quad \text{High Type} \tag{32}$$

$$(1-0.8)\frac{(25-5)^{(1+3.4)}}{1+3.4} + 0.8\frac{(16.2-5)^{(1+3.4)}}{1+3.4} < \frac{16.2^{(1+3.4)}}{1+3.4} \quad \text{Low Type} \tag{33}$$

Comparing this partial separating equilibrium with the complete separating equilibrium, we have more high-type workers pooled as non-degree workers, and the wage offers to non-degree workers are consequently higher. [21]

In light of the importance of risk attitudes, I use the classical binary lottery tasks to measure subjects' risk preferences, and then test if they can indeed explain subjects' choices as workers in the lab experiments. Previous laboratory researches on subjects' risk attitudes, such as Holt and Laury (2002), Hey and Orme (1994) and Harrison and Rutström (2008), generally find small to modest risk aversion among subjects in the laboratory environment, with stakes similar to what will be used in my experiment. Also, by the design of the experiment as will be introduced in details later, I will be able to observe each subject's decisions as both high-type and low-type workers, so comparing signaling decisions made by the *same* subject between the two types will be equivalent to holding risk attitudes the same between ability types. To make comparisons across different

[20] Since we have $F(-3.4) = 0$ and the left hand side of equation (16) increases with r^i, it safices to show that low type workers with $r^i = -3.4$ will not pursue the degree.

[21] Note this partial separating equilibrium due to heterogeneous risk attitudes is different from the hybrid equilibrium when all workerers risk neutral workers, where $e_h = 0.34$ and $e_l = 0$.

subjects, risk attitudes are elicited from each subject after they are done with the signaling game and will be used to explain between-subject differences in wage offers and education choices.

III. Experiment Design

The experiments are designed to test the model developed above and to answer the following questions: Will subjects learn to play the separating equilibrium in this labor market? Will the market reach the separating equilibrium more often when pooling not to pursue is unintuitive? Do risk preferences have any effects on subjects' decisions as workers and as employers? In the experiments reported in Kübler et al. (2008), education costs are higher for low types and there is no dropout risk. Their experiments can be seen as a parametrization of the model developed in Section 2, in which $\lambda_h = \lambda_l = 0$ and $c_h > c_l > 0$.[22] To focus on the role that the type-dependent dropout risks play in inducing separation, the education costs are kept the same for both types of workers in the current design, that is, $\lambda_l > \lambda_h > 0$ and $c_h = c_l = c > 0$.

Varying the education cost c and the share of low type workers in the population μ, while keeping workers' productivities and dropout risks constant, we have five treatments, summarized in Table 1. In treatments 1, 2 and 3 at the top half of Table 1, education costs are kept constant, while the share of low types in the worker population decreases linearly by 25%. Therefore, I refer to them as *Population Treatments*. In treatments 4, 2 and 5 at the bottom half, the share of low types is kept constant, while education costs increase linearly by \$2. Therefore, I refer to them as *Cost Treatments*. Note that Treatment 2 is at the center of both treatment groups and will serve as the baseline for pairwise hypothesis tests later.

[Table 1 about here.]

[Table 2 about here.]

In all five treatments, pooling not to pursue and separating are both Perfect Bayesian Equilibria, while pooling to pursue is not; therefore, "pooling" refers to "pooling not to pursue" in the discussion hereafter. However, the five treatments differ in whether pooling is unintuitive and subject to the refinement by the Cho-Kreps Intuitive Criterion; Table 2 applies the Intuitive Criterion to the

[22] The procedures used in the current experiments are very similar to those in Kübler et al. (2008); therefore, the results in Kübler et al. (2008) can lend some insights in the discussion of the results from the current experiments.

pure-strategy pooling equilibrium of these treatments. The row labeled "Pooling Wage" shows the wage offer to workers without the degree from risk-neutral employers in the pooling equilibrium; the next two rows show the expected payoff of each type should employers offer \$25, the highest possible wage, to workers who deviate from pooling and successfully earn the degree, net of the corresponding signaling cost in each treatment. In the first two treatments (columns) of each treatment group, pooling is unintuitive since deviation yields a lower expected payoff for the low type even under the most favorable out-of-equilibrium wage offer, while the high type can get a higher expected payoff. In the last treatment of each treatment group, neither type can profit from deviation in expectation, and pooling cannot be refined by the Cho-Kreps Intuitive Criterion.

Previous signaling experiments have shown that the separation between the high and low type's signaling decisions was never 100%. The purpose of these treatments is to see if changes in share of low types in the population or signal cost will make separation more or less complete. In addition, within each treatment group, although the changes in the treatment parameter are linear, pooling equilibrium is unintuitive in the first two treatments but intuitive in the last treatment. Therefore, with this design, the effectiveness of the Intuitive Criterion will manifest as a more dramatic increase in pooling (or, equivalently, a much less complete separation) when the cost changes from \$5 to \$7 than when it changes from \$3 to \$5 in the Cost Treatments, and when the share of low types in the population changes from 50% to 25% than when it changes from 75% to 50% in the Population Treatments.

Ten sessions were conducted between December 2015 and March 2017 in the lab at Georgia State University's Experimental Economics Center. A total of 240 subjects were recruited from among the undergraduate students at the university. The experiments are run using ZTREE programs. Each session lasted approximately two hours. Twenty-four subjects participated in each session and two sessions were conducted for each treatment. The market parameters were fixed within each session. To avoid potential confounding effects from contexts such as "academic degree", "employers" or "workers", we used neutral wording in the experiments. Workers are referred to as sellers who are selling products with either high values or low values, and employers are referred to as buyers who are bidding for the products. Pursuing the degree is described as testing the product, and the degree itself is referred to as a quality certificate. The subject instructions for Treatment 2 are attached as Appendix D.

In each session, the subjects play the signaling game for 32 periods; the 32 periods are divided into 4 blocks $\times$ 8 periods per block, and each subject assumes the same role within a block but might switch roles between blocks. The block and role switch design is common in signaling experiments: it allows us to observe each subject's decisions as both buyer and seller; and it can help prompt subjects understanding of the game from different angels.[23] Table 3 shows a decomposition of the block design and role assignment rules within each session.

[Table 3 about here.]

When each period begins, each seller will get one product with either a high or a low quality. Then, two buyers will be randomly and anonymously matched with the seller to undergo a first-price sealed-bid auction on her product.[24] The qualities of the products that each subject gets to trade are assigned in the following way (using Treatment 2, where half of the products have low qualities, as an example):

1. In each period, half of the eight sellers will get the high-quality products and the other half will get the low-quality products. This information is *included* in the instructions.

2. In the eight periods of each block, each seller will get high-quality products in four periods and low-quality products in the remaining four periods; each buyer will be matched with high quality sellers in 4 periods and with low quality sellers in the remaining 4 periods. This information is *excluded* from the instructions, and the sequences of product qualities that a subject gets to trade do not follow any patterns. Since subjects do not know the specifics of the block and role switching design, the possibility that they will figure out the sequence of quality assignments over the 32 periods is minimal.

With this method of assignment, we can make sure to get observations for each subject on signaling behavior when selling high- and low-quality products. So, for each parameterization, we can make within-subject comparisons on signaling rates (that is, the frequencies of a seller taking the test) given different product qualities. Also, since the population distribution is the key treatment

[23] As will be introduced later, one of the 32 periods will be chosen to determine their payoff. Under the assumption that agents are expected utility maximizers, the role switching and block design combined with this payoff mechanism should not create incentives for portfolio decisions. See Cox et al. (2015) for an extended discussion on the comparability between this payoff mechanism and expected utility theory.

[24] Matching sellers and buyers to form individual markets is a popular feature of recent experiments, such as de Haan et al. (2011), Jeitschko and Normann (2012) and Kübler et al. (2008), while a representative example of using a double auction in a pit market is Miller and Plott (1985). The main reason to use matching in the current experiments is to apply random matching among subjects to make each period as close as possible to a one-shot game.

parameter in the Population Treatments, we want to avoid subjects' suspicions on this parameter should a subject experience unusually high or low frequencies of low-quality products.

As soon as the subject matching and product assignment are done, each seller is informed of the quality of her product and is asked to decide whether to test her product. If a seller decides to take the test, a horizontal bar that is divided into success zone and failure zone shows up on the computer screen. A white needle appears and runs across the bar randomly for five seconds. If the needle rests in the failure zone, the product fails the test; if in the success zone, the product passes the test. The failure zone takes up 10% of the bar for the high-type product and 90% for the low type. After all sellers are done with decisions and tests, each product will be put on the market in which it belongs; if a sellers decides to test and the product passes, it will be put on the market with a certificate. The two buyers will be informed whether the product in their market is certified[25] and will then each submit one bid without knowing the other's bid. The product will be sold to the buyer with the higher bid, at a price equal to his own bid. Subjects will then be informed of the two bids and the quality of the product in their market, as well as their own profits in the current period, calculated as in Table 4, using Treatment 2, where the cost to take the certification is $5, as an example.

[Table 4 about here.]

After 32 periods of market trading, one period will be randomly chosen to determine all subjects' payoffs. The experiment will then proceed to the second part, in which the subjects need to choose a preferred lottery for each of the 20 lottery pairs we present to them.[26] The 20 lottery pairs are carefully chosen to have good coverage in the Marschak-Machina (MM) triangles (two pairs will have either common ratios or common consequences), so as to allow robust inference on subjects' risk preferences. Each pair is graphed in its corresponding MM triangle in Figure A.1. The 20 pairs of lotteries are presented to each subject, one pair at a time; the order of the lottery pairs, as well as the positions of the two lotteries in each pair on the computer screen, are individually randomized for each subject. After a subject chooses her preferred lottery in one pair, the chosen lottery will be played out immediately before proceeding to the next choice. After subjects have

[25] Buyers will not be informed of sellers' decisions, and this is commonly known to all subjects.

[26] At the beginning of each session, subjects are informed that there will be a second part in which they can still make money, but not informed of the nature of the tasks in the second part.

made all 20 choices, the payoff from one choice will be randomly chosen to determine their payoff in the second part of the experiment.[27]

At the end of each session, subjects are asked to fill out a demographic survey and are paid the sum of their payoffs from both parts of the experiment, plus a show-up fee of $5. A summary of age, gender, GPA and ethnicity of the subjects in each session can be found in Table B.1.

IV. Data and Results

In this section, I first describe seller and buyer behavior with summary statistics and hypothesis tests; then, using different regression specifications, I explore how subjects' behavior changes as they gain more experience in playing the game, and whether their risk preferences affect their signaling strategy as sellers and bidding strategy as buyers. I provide only the major tables and graphs, and include the other tables and graphs in the appendices.

4.1 Individual Behavior

For each subject, I create the following four variables to summarize her decisions throughout the 32 periods of market trading: (1) signaling rate (defined as frequency of taking the certification test) when selling high-quality products S_H; (2) signaling rate when selling low-quality products S_L; (3) average bids on certified products B_C; and (4) average bids on non-certified products B_{NC}. For the 48 subjects in each treatment, the empirical distributions of signaling rates by product quality, S_H and S_L, are shown in Figure 1, and the empirical distributions of average bids by certification status, B_C and B_{NC}, are shown in Figure 4. Also, the means on these variables over the 48 subjects in each treatment are reported in Table 5.

[Table 5 about here.]

Starting with seller behavior, I find evidence supporting the separating strategy[28] among sellers, although similar to what has been observed in other signaling experiments, the separation is

[27]The payoff mechanisms in both parts are the $\mathrm{POR}_{\mathrm{PAS}}$ payoff mechanism introduced by Cox et al. (2015). Using the same set of decision tasks, their paper compares subjects' decisions made under different payoff mechanisms to those made without the possibilities of cross-task contaminations (the "One-Task" treatment where each subject makes only one decision on one of the five decision tasks). They found that compared to other payoff mechanisms, the subjects' decisions under the $\mathrm{POR}_{\mathrm{PAS}}$ mechanism are most similar to those in the "One-Task" treatment.

[28]This refers to the seller strategy that taking the test when selling high-quality product and not taking the test when selling low-quality ones.

incomplete. Based on the Wilcoxon paired signed-rank tests on S_H and S_L among the 48 subjects in each treatment, the null hypothesis that sellers take the test at the same frequencies when selling high- and low-quality products can be rejected for all treatments. The alternative hypothesis that the sellers take the test more frequently when selling high quality product is supported in all treatments:

$$S_H > S_L \text{ in all treatments, significant at the 1\% level.}$$

However, the empirical distributions of S_H and S_L show different degrees of separation in the five treatments. Figure 1 shows the histograms of signaling rates by product quality for the 48 subjects in each treatment; the Population Treatments are aligned vertically and the Cost Treatments are aligned horizontally. Treatments with an unintuitive pooling equilibrium are located in the top, left and center panels; in these treatments, there is a clearer separation between the high type's and the low type's distributions: the high-type sellers (the bars with blue solid outlines) are concentrated in the right and closer to the 100% point, while the low-type sellers (the bars with red dashed outlines) are in the left and closer to the 0% point. In contrast, in treatments with an intuitive pooling equilibrium, shown in the right and bottom panels, the distributions of the two types overlap, mainly due to the leftward shift of the high type's distribution, indicating more pooling than in the other three treatments. The means of these distributions are reported in the columns under "Signaling Rate" in Table 5, and the trends of their changes across treatments are graphed by treatment groups in Figure 2.

The observations discussed above are generally supported by two sample Wilcoxon rank-sum tests on S_H and S_L between treatments. Using Treatment 2 (50% and \$5 treatment, the middle panel of Figure 1) as the baseline, low-type sellers do not behave differently in other treatments, with one exception: the null hypotheses that ${S_L}^{50\%,\ \$5} = {S_L}^{50\%,\ \$7}$ is rejected at 1% in support of ${S_L}^{50\%,\ \$5} > {S_L}^{50\%,\ \$7}$. In contrast, high-type sellers in treatments with intuitive pooling signal less frequently than high-type sellers in Treatment 2, and high-type sellers in treatments with unintuitive pooling do not show a significant difference:[29]

$${S_H}^{75\%,\ \$5} = {S_H}^{50\%,\ \$5} >^{***} {S_H}^{25\%,\ \$5}$$

$${S_H}^{50\%,\ \$3} = {S_H}^{50\%,\ \$5} >^{***} {S_H}^{50\%,\ \$7}$$

[29]The same results hold under the two sample t-tests and Kolmogrov-Smirknov tests with one exception: paired t-tests can reject ${S_H}^{50\%,\ \$3} = {S_H}^{50\%,\ \$5}$ at the 5% level.

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

As a measure on the degree of separation in their strategies as sellers, the difference between the signaling rates when selling high- and low-quality products is calculated as $S_{DIFF} = S_H - S_L$ for each subject; the distribution of S_{DIFF} among the 48 subjects in each treatment is in Figure A.2, and the means are reported in Table 5. Pairwise Wilcoxon rank-sum cannot reject the null hypothesis that S_{DIFF} is identically distributed in the three treatments with an unintuitive pooling equilibrium. However, when we compare the treatments with intuitive pooling to Treatment 2, the tests strongly support the alternative hypothesis that the difference in signaling rates between high- and low-quality products becomes smaller:[30]

$$S_{DIFF}{}^{75\%,\ \$5} = S_{DIFF}{}^{50\%,\ \$5} >^{***} S_{DIFF}{}^{25\%,\ \$5}$$

$$S_{DIFF}{}^{50\%,\ \$3} = S_{DIFF}{}^{50\%,\ \$5} >^{***} S_{DIFF}{}^{50\%,\ \$7}$$

Conclusion 1: Signaling Behavior *In all treatment, sellers signal more frequently when selling high-quality products. Nevertheless, compared to treatments with unintuitive pooling, as the pooling equilibrium becomes intuitive due to an increase in cost or a decrease in the share of low-quality products, the high-quality sellers signal less frequently; as a result, the difference in signaling rates between high- and low-quality products is smaller as the pooling equilibrium becomes intuitive.*

As a result of lower signaling rate among high-type sellers, the share of the high (low) type among non-certified products are higher (lower) in treatments with an intuitive pooling equilibrium. For each individual subject, two variables are created to represent the correlation between the certification status and product qualities that she bid on as buyer: the share of low-quality products among the certified products μ_1, and the share of low-quality products among non-certified products μ_0. The means of these two variables over the subjects in each treatment are reported in the columns under "Share of Low Type" in Table 5. [31] The distributions of these variables are sharply concentrated around their means, so the histogram is only supplemented as Figure A.4.

The share of low-quality products among certified products μ_1 is very close or equal to 0 in all treatments. The share among non-certified products μ_0 drops *monotonically but not linearly* (solid

[30]The same results hold under the two sample t-tests, but Kolmogrov-Smirknov tests can reject $S_{DIFF}{}^{75\%,\ \$5} = S_{DIFF}{}^{50\%,\ \$5}$ at 10% level.

[31]The market share of certified products in each treatment is also reported in Table 5.

lines in Figure 3) as the population share of low types drops or the cost increases *linearly*. This is caused by a similar non-linear drop of the signaling rate among high-quality sellers (solid blue lines in Figure 2). The kinks at the mid-point of the lines, where pooling goes from unintuitive to intuitive, suggest the effectiveness of the Cho-Kreps Intuitive Criterion on equilibrium selection. Theoretical predictions on μ_0 under complete pure-strategy separation, that is, when the high type always take the test and the low type never takes the test, are included as the reference lines (dashed lines in Figure 3). A bigger distance between the solid line and the dashed line means that the market deviated further from complete separating, and that more high and low types are pooled as non-cerified products.

Conclusion 2: Effectiveness of the Intuitive Criterion *Consistent with the predictions of the Intuitive Criterion, there is dramatically less pooling between the high and low types as non-certified products when the pooling equilibrium is unintuitive. The certified products are predominantly high-quality products in all markets because of the low signaling rates and high failure rate among low-quality products.*

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

Turning to buyer behavior, Figure 4 shows the empirical distributions of average bids on certified and non-certified products over the 48 subjects in each treatment, and the means are reported in the "Average Bidding" columns in Table 5. The bidding premium on certified products by each subject – that is, the increase in a subject's average bid on certified, compared to that on non-certified products – is measured as $B_{DIFF} = B_C - B_{NC}$. The distributions are shown in Figure A.3, and the means are also reported in Table 5.

The first observation is that the average bids (reported in Table 5 and Figure 4) are generally lower than the expected values of the products given the empirical posterior distributions (reported as μ_0 and μ_0 in Table 5) in each treatment. This is potentially caused by risk aversion and by the optimal strategy for a subject to bid below her true valuation of the auction object in the first-price sealed-bid auctions[32]. Therefore, rather than comparing bids and prices to the predictions

[32] With the same market institution, Kübler et al. (2008) also observe that bids generally do not converge to the predicted value in a pure-strategy separating equilibrium; however, by increasing the number of buyers to three, the bids increase

when risk neutral buyers truthfully reveal their valuations of the product, I focus on comparing bids between certified and non-certified products within each treatment, as well as comparing bids on the certified/non-certified products across treatments.

Starting with bidding behavior in the Population Treatments, I observe an increasing trend in bids on non-certified products as the population share of the low type decreases: from the top to the bottom panels in Figure 4, the distribution of bids on non-certified products shifts to the right, while the distribution of bids on certified products shifts slightly to the left. This pattern is generally confirmed with pairwise Wilcoxon rank-sum tests:

$$B_{NC}{}^{75\%,\ \$5} <^{***} B_{NC}{}^{50\%,\ \$5} <^{***} B_{NC}{}^{25\%,\ \$5}$$

$$B_{C}{}^{75\%,\ \$5} >^{**} B_{C}{}^{50\%,\ \$5} <^{***} B_{C}{}^{25\%,\ \$5}$$

Two factors could drive up the bids on non-certified products as μ decreases: the buyers are updating their posterior beliefs properly in response to more pooling behavior among sellers; and/or they are simply responding to the lower proportion of low types in the prior distribution of the products. In Figure 5, I graph the means of B_{NC} across treatments as the solid red line and provide two reference lines: the dashed gray line marks the expected value given the posterior distribution of non-certified products observed in each treatment, and the dotted gray line marks the expected value given the posterior in the pure-strategy separating equilibrium. Focusing on the changes in B_{NC} in Population Treatments in the left panel of Figure 5: the slope of the solid red line is greater than that of the dotted gray line but smaller than that of the dashed gray line, indicating partial but incomplete posterior updating among buyers in response to more pooling behavior among sellers. That is, buyers do respond to changes in seller's strategies across the treatments, and the increase in B_{NC} is not *solely* due to the change in the share of low types in the prior distribution of the products.

[Figure 4 about here.]

[Figure 5 about here.]

Driven mainly by the increase in bids for non-certified products, the bidding difference drops as the share of low types decreases from 75% to 50%, holding the cost constant at \$5. This is

significantly. The conjecture can be tested by switching to alternative institutions, such as a second-price sealed-bid auction or an English auction, in which buyers are predicted to bid their true valuation of the auction object–that is, the certainty equivalents based on their risk attitudes and beliefs.

consistent with the increased pooling behavior among sellers and the decreased separation between high- and low-type products. However, there is no such drop when the share of low types drops further from 50% to 25%. [33]

$$B_{DIFF}{}^{75\%,\ \$5} >^{***} B_{DIFF}{}^{50\%,\ \$5} = B_{DIFF}{}^{25\%,\ \$5}$$

Turning to bidding behavior in Cost Treatments: based on the observed share of low type among non-certified products (μ_0 reported in Table 5), since μ_0 does not change much when the cost changes from \$3 to \$5, bids on non-certified products should be similar between these two treatments; μ_0 drops by 14% when the cost increases further from \$5 to \$7, so bids on non-certified products should increase accordingly. These predictions are graphed as the dashed gray line in the right panel of Figure 5.[34] The observations are only partly consistent with the above predictions, as is shown in Figure 4: consistent with the prediction, as the cost increases (from the left to the right panels), the distribution of B_{NC} does not shift much from the \$3 to \$5 treatment; however, it also does not shift much from the \$5 to \$7 treatments, when it should have shifted to the right according to the prediction. I observe similar trends when comparing the means of B_{NC} in these three treatments (the solid red line) in the right panel of Figure 5. Pairwise Wilcoxon rank-sum tests cannot reject that the bids on non-certified products are the same in the Cost Treatments:

$$B_{NC}{}^{50\%,\ \$3} = B_{NC}{}^{50\%,\ \$5} = B_{NC}{}^{50\%,\ \$7}$$

Another observation that is inconsistent with posterior updating is that the distribution of bids on certified products shifts to the left when the cost increases from \$5 to \$7, which should not happen since the posterior distribution of certified products is basically the same between these two treatments. The observations are also backed up by pairwise Wilcoxon rank-sum tests:

$$B_{C}{}^{50\%,\ \$3} >^{***} B_{C}{}^{50\%,\ \$5} >^{***} B_{C}{}^{50\%,\ \$7}$$

Although B_{NC} and B_C do not always change consistently with increased pooling, their joint effect is a significant decrease in the bidding premium on certified products, B_{DIFF}, which turns out

[33] While results from Kolmogorov-Smirnov tests are the same, two-sample t-tests can reject $B_{DIFF}{}^{50\%,\ \$5} = B_{DIFF}{}^{25\%,\ \$5}$ at the 10% level.

[34] Since the share of low types in the prior distribution is fixed at 50%, the expected values of non-certified products in *pure-strategy separating equilibrium* is constant and is shown as the dotted gray line.

to be consistent with the increase in pooling between high- and low-type products when the cost increases:

$$B_{DIFF}{}^{50\%,\ \$3} >^{***} B_{DIFF}{}^{50\%,\ \$5} >^{***} B_{DIFF}{}^{50\%,\ \$7}$$

Despite the decreased difference in bids when the cost increases and when share of the low type decreases, Wilcoxon paired signed-rank tests reject the null hypothesis that average bids on certified and non-certified products are the same in all five treatments:

$$B_C > B_{NC} \text{ in all treatments, significant at the 1\% level.}$$

Conclusion 3: Bidding Behavior *Buyers bid significantly higher on certified products than on non-certified products in all treatments. As the population share of the low type decreases, bids on non-certified products increase, and bids on certified products decrease slightly; as the cost of the certification test increases, bids on non-certified products stay the same, and bids on certified products decrease. As a result, the individual bidding premium on certified products generally drops as μ decreases or as cost increases, consistent with increased pooling between high- and low-quality products (Conclusion 2).*

Prices of certified and non-certified products are also reported in columns "Average Price" of Table 5. As one would expect, the prices changes across treatments in a similar pattern to bids: the price premium of certified products (defined as the price difference between certified and non-certified products) drops as the share of the low type decreases or as the cost of the certification test increases. In connection with seller behavior, Table 6 shows, for each product type, the expected payoff of sellers when they signal (take the certification test) and when they don't, based on the average prices in each treatment. The signaling rate of high-type sellers is, indeed, positively correlated with their expected gain from signaling (the "Difference" column).[35]

An interesting question to ask, given the role switching design of this experiment, is whether an individual's strategy as a seller correlates with her own strategy as a buyer. A simple way to answer this question is to find the correlation coefficients between the differences in signaling rates S_{DIFF} and bidding premiums B_{DIFF} among the 48 subjects in each treatment. The results are reported in Table 7. If the beliefs about others' strategies come from a subject's own perception of the game and choice of strategies, we will expect B_{DIFF} to be positively correlated with S_{DIFF} within each

[35]However, the table also shows that sellers are taking the test with positive frequencies even when the expected payoffs are negative. This indicates that they are either risk loving when they make signaling decisions, or that sellers do not fully adjust to the market prices in their investment decisions.

treatment. Such correlations are found in all treatments except for Treatments 1; in addition, the correlation is of greater magnitude in treatments where pooling cannot be refined by the Cho-Kreps Intuitive Criterion (0.485 in Treatment 3 and 0.571 in Treatment 5). I further decompose these correlations in terms of the bidding behavior on certified and non-certified products, and find that they mostly caused by positive correlation-ships between B_C and S_{DIFF}.

[Table 6 about here.]

[Table 7 about here.]

4.2 Regression Analysis

To see how subjects learn to play the game, as well as how their risk preferences correlate with their decisions as buyers and sellers, I report random effects panel regression results on signaling and bidding decisions in Tables 8 and 10, with errors clustered at the subject level. Using observations within each treatment, I run logit regressions on sellers' decisions of whether or not to signal (take the certificate test) in each period with three sets of explanatory variables, and I arrange the results by treatment groups in Table 8 for ease of comparison. The models with product type as the only explanatory variable (first three columns) are consistent with the hypothesis tests and Conclusion 1: the coefficients are all positive at the 1% significance level, and generally decrease as the share of low types drops in the Population Treatments or as the cost increases in the Cost Treatments. To directly test if the changes in the coefficients are significant, I run panel regressions on subjects signaling behavior separately for high and low quality products, with 50%, \$5 session as baseline session and dummies for other treatments, and with errors clustered at the subject level. The results are reported as Table 9 and further confirm the previous comparisons on signaling rates across different treatments.

When I add the number of current periods interacted with product type to the set of control variables (the middle three columns), I find that, subjects learn to signal more often when selling high-type products in the three treatments with an unintuitive pooling equilibrium, but do not in treatments with an intuitive pooling equilibrium.[36] The last three columns in Table 8 report the

[36]Given the experimental design as demonstrated in Table 3, I compare the signaling behavior of subjects who played as seller in the first and last blocks. I calculate each subject's signaling rates S_H, S_L and S_{DIFF} in the first and last block, and report the means over all subjects within each treatment in Table B.2. To test for the differences in the distributions of these variables between the two blocks, I perform Wilcoxon Signed-Rank tests on these variables. I find that when selling

random effects panel regression results, which include the number of safer lotteries[37] that subjects choose in the 20 lottery pairs as the control variable for risk preference. The signs of the coefficients are significantly negative in two out of three treatments with unintuitive pooling, as predicted in the discussion on risk attitudes in the Model Section: the more risk-averse a subject is, the less likely it is that she will choose to take the test. In contrast, risk attitudes do not significantly affect sellers' decisions in the two treatments where pooling is intuitive.

Similarly, I fit three specifications of linear regression models on bids in each treatment, which are reported in Table 10. The first three columns are models that include certification status as the only explanatory variable, and the results are consistent with the hypothesis tests and Conclusion 3.[38] Then, I add the interaction term between period and the product type (the middle three columns), and the results show an increasing trend in the bids. Also, subjects learn to bid more on certified products in Treatments 2 (50%, \$5) and 4 (50%, \$3), while learning to bid more on non-certified products in all other treatments. I do not observe any coefficients to be significantly negative. This suggests generally increased competition among buyers.[39] Except in Treatment 3 (25%, \$5), there is no significant changes in bidding behavior due to risk attitudes after adding number of safe choices in the linear specification.[40]

As robustness check, I also run regressions on the signaling and bidding behavior, pooling observations from all five treatments (Treatment 2 as the baseline, errors clustered at the subject level)

high type products (S_H), subjects signal more often in the last block than in the first block in two of the three treatments with unintuitive pooling, but not so in either of the two treatments with intuitive pooling. I find no significant difference in signaling behavior between the first and last blocks when selling low type products (S_L), except for in Treatment 5. I also find that, compared to the first block, the difference in signaling rates $S_H - S_L$ becomes greater in the last block in all three treatments with unintuitive pooling, but not so in the two treatments with intuitive pooling.

[37]The safer lottery in a pair refers to the one positioned left in the MM triangle. Under the Expected Utility Theory, indifference curves are linear in the MM triangles. Also, the more risk averse an individual is, the steeper her indifference curve, and therefore, the more likely she chooses the lottery positioned left from a given lottery pair.

[38]To directly test if these changes, I also report panel regressions on subjects bidding behavior separately for certified and non-certified products in Table 11, with 50%, \$5 session as baseline and dummies for other treatments, and with errors clustered at the subject level.

[39]I calculate average bids of each subject in the first and last blocks of the experiment on certified products B_C, on non-certified products B_{NC} and also on the bidding premium for certified products B_{DIFF}, and Table B.3 reports the means of these three variables in the first and last blocks of each treatment, as well as the differences between the two blocks. Within each treatment, I test for the differences on the distributions of these three variables between the first and last blocks using Wilcoxon Signed-Rank tests. Compared to their counterparts in the first block of experiments: average bids on certified products B_C are significantly higher in the last blocks of all treatments; average bids on non-certified products B_{NC} are also significantly higher in the last blocks of all treatments except for in Treatment 4; and the bidding premium $B_C - B_{NC}$ are higher in the last blocks of the treatments where pooling is unintuitive, all significant except for Treatment 1.

[40]A possible cause of this result is that when subjects make decisions in the lottery task, they already know their payoff from the first part of the experiment, so the changes in wealth level might lead to changes in risk attitude. The insignificance could also possibly be caused by the linear specification between bids and number of bids, and a structural model based on the optimal bidding function might be needed to look further into this matter.

and using four sets of explanatory variables. Tables B.4 and B.5 report the full regression results with controls on demographic variables. Most demographic variables do not have any significant effects in subjects' behavior, with only a handful of exceptions.

Table 9 reports the regressions on signaling rates for low- and high-type sellers, respectively. The treatment effects are generally consistent with those found from the hypotheses tests and panel regressions on signaling behavior, whether or not we add period or the number of safe choices as control variables. In contrast to the panel regression results of each treatment, I find here that subjects learn to signal less often when they sell low-quality products, and I find no learning effects when they sell high-quality products. The coefficients of the risk attitudes variable suggest that more risk averse sellers signal less frequently when selling low type products, but not so when selling high type products.

Table 11 shows the regression results for bids on non-certified and certified products, respectively. The treatment effects are also consistent with the results from hypotheses tests and panel regressions. The coefficients of the period are significantly positive in all treatments and are greater for bids on certified products than on non-certified products. This is consistent with the finding from panel regressions that competition among buyers tends to increase as the experiment continues, and more so among buyers of certified products.

[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

[Table 11 about here.]

V. Concluding Remarks

In pursuing an academic degree, people face different risks of dropout due to differences in their abilities. Inspired by this observation, I developed a general signaling model by introducing type-dependent noises into a simplified Spence model. Previous research on stochastic signaling models commonly assumes the same distribution of noises across different types, and relies on different costs across the types to induce signaling behavior in a separating equilibrium. In contrast, the current paper relaxes the type-dependent costs assumption and highlights the role of type-dependent noises in inducing separation, when signaling costs cannot be effectively differentiated between different types of senders.

Both the theoretical analysis and the experimental results have shown that, when there is a chance that the signal might be blocked, if the more desirable type of senders have higher chances of successfully sending the signal, a separating equilibrium exists under certain conditions, even if we relax the assumption on signal costs and assume sending the signal is equally costly regardless of sender type. The paper also provide lab evidence that supports the effectiveness of the Cho-Kreps Intuitive criterion: in treatments where pooling is unintuitive, I observe dramatically less pooling in both senders' and receivers' behavior; in addition, I observe more separating in senders' decisions as the experiment continues and as subjects gain experience, but only in the unintuitive pooling treatments.

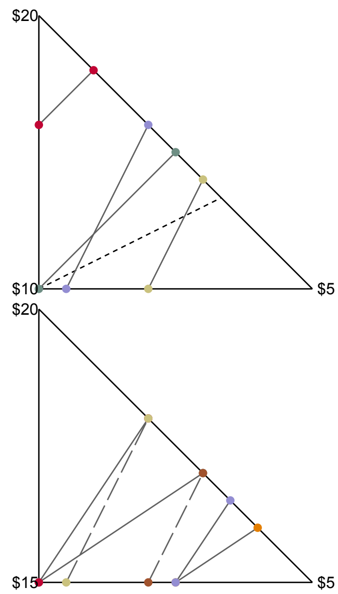
This paper also shed light on the effects of subjects' risk preferences on their strategies in stochastic signaling games. To infer their risk preferences, I observe subjects' choices in a different decision task, the classical binary lottery tasks, and count the number of safe lotteries chosen by each subject to measure the level of her risk aversion. I find some evidence on the connection between subjects' risk preferences and strategies as sellers in the signaling game: the more risk averse subjects are less likely to send the signal as sellers, especially when selling low-quality product. The connection between risk preference and bidding strategy is unclear; to further explore this connection, a closer look with a structural model based on the optimal bidding function of risk averse bidders may be an interesting extension.

Developed in the context of job market signaling, the paper aims to bring new insights to settle the contest between human capital and education signaling models in explaining wage differentials associated with higher education. If the risk of dropout weighs in on people's enrollment decisions and can cause a similar self-selection process discussed by Spence, then we should pay due attention and gather data on this variable when we decompose the role of education in signaling and improving productivity. For instance, a testable hypothesis from the model is that, between two programs that offer similar curricula and training, we would expect graduates from the one with more stringent degree requirements to have a bigger premium on wages due to more significant signaling effects.

Admittedly, the simplicity of the model developed in the current paper allows for a cleaner test but also limits its applications in addressing more complex questions. To make the model more realistic, an interesting extension for future research would be to develop a dynamic model by breaking down the graduation process and examining the costs and dropout risks that students face each year. In a different vein, more experiments can be run to determine the effects of market institutions on equilibrium, specifically, on the level of product prices and the price premium of certified products.

A. Appendix Figures

Figure A.1: 20 Lottery Pairs Displayed in Machina-Marschak Triangles



[1] Each lottery is represented by a dot in the corresponding Triangle
[2] The two lotteries connected by a cord represent a pair from which the subjects need to choose a preferred lottery.
[3] The dashed line is the equal-expected-value line, that is, the lotteries connected by the dashed line have the same expected values. The dashed line in the MM triangle with prizes $20-$10-$5 is added as a reference; no lotteries pair along the line is actually presented to subjects.

Figure A.2: Difference in signaling rates per Seller

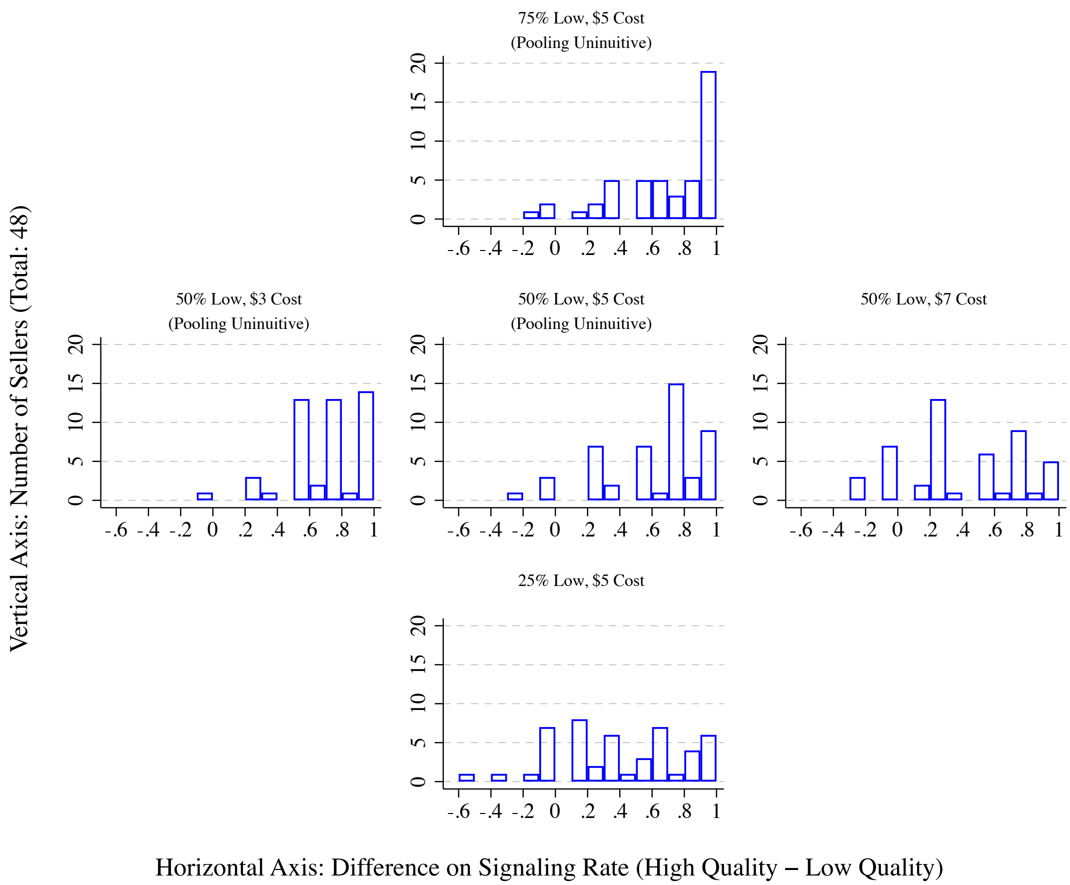


Figure A.3: Difference in Average Bids per Buyer

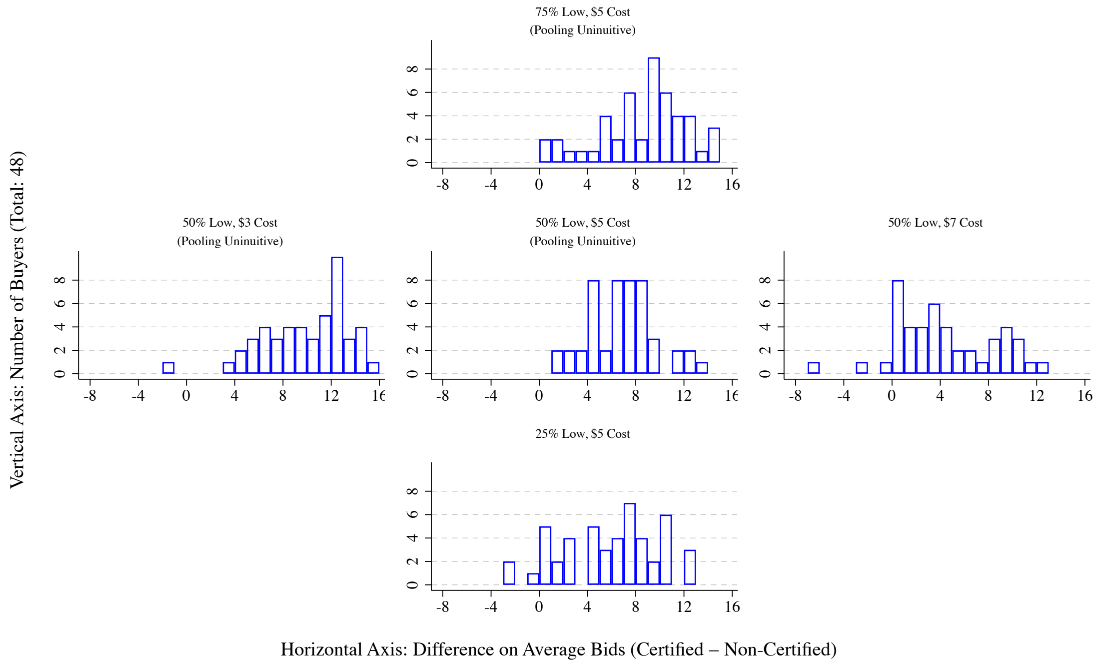
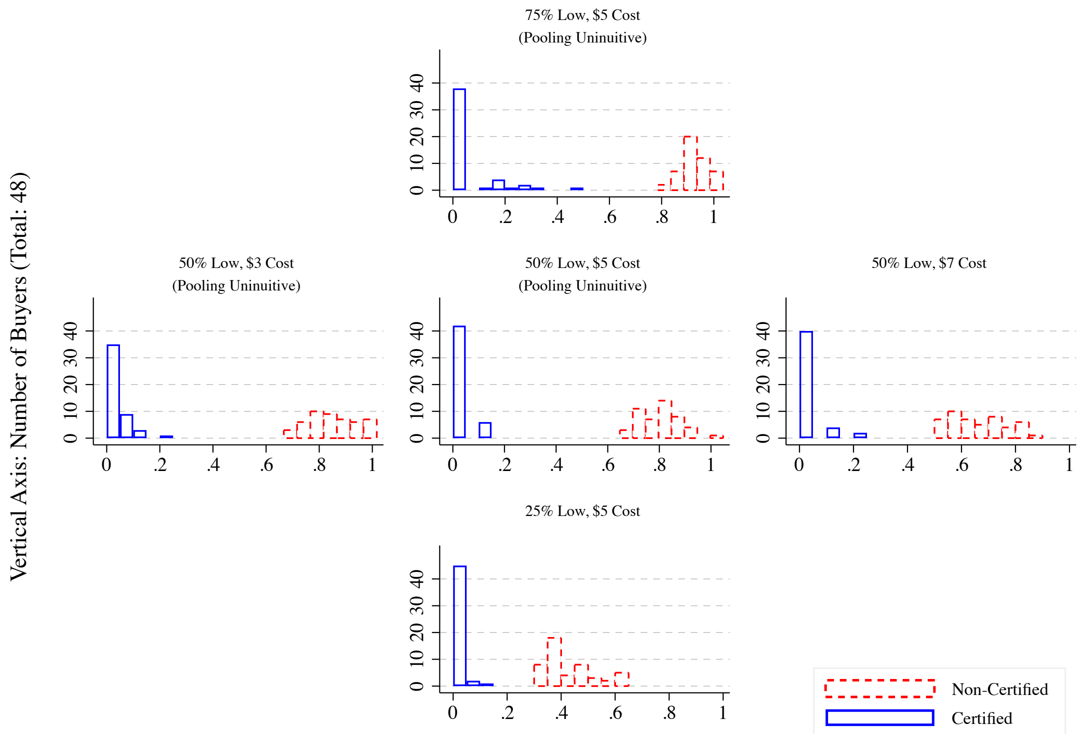


Figure A.4: Share of Low Quality Products Encountered per Buyer (By Product Certification)



Horizontal Axis: Proportion of Low Quality Products Encountered by Each Buyer
By Certification Status

B. Appendix Tables

Table B.1: Demographics of Subjects in Each Treatment

Treatment		1	2	3	4	5
Total Subjects		48	48	48	48	48
Female		26	20	32	30	31
No Experience		23	19	25	27	16
Age		19.7	20.6	20.4	19.7	19.9
Race	African American	30	26	30	31	26
	White	5	3	5	6	6
	Asian	11	14	7	5	8
	Hispanic	1	4	2	1	2
	Other or Prefer Not to Answer	1	1	4	5	6
GPA	< 2.0	1	0	2	0	0
	2.0-2.99	7	10	10	17	11
	3.0-3.49	21	18	21	18	19
	3.5-4.3	19	20	15	13	18

Table B.2: Comparison of Signaling Rates in the First and Last Blocks of Each Treatment

Treatment	Pooling is Unintuitive	Signaling Rates (%)								
		High Type S_H			Low Type S_L			Difference S_{DIFF}		
		1^{st} Block	4^{th} Block	Difference	1^{st} Block	4^{th} Block	Difference	1^{st} Block	4^{th} Block	Difference
1	Yes	75.0	90.6	15.6	13.5	6.3	-7.3	61.5	84.4	22.9 *
2	Yes	70.3	85.9	15.6 ***	12.5	9.4	-3.1	57.8	76.6	18.8 ***
3	No	66.7	67.7	1.0	15.6	9.4	-6.3	51.0	58.3	7.3
4	Yes	76.6	92.2	15.6 *	26.6	23.4	-3.1	50.0	68.8	18.8 *
5	No	53.1	43.8	-9.4	12.5	4.7	-7.8 *	40.6	39.1	-1.6

Table B.3: Comparison of Average Bids in the First and Last Blocks of Each Treatment

Treatment	Pooling is Unintuitive	Average Bids ($)								
		Certified B_C			Non-Certified B_{NC}			Difference B_{DIFF}		
		1^{st} Block	4^{th} Block	Difference	1^{st} Block	4^{th} Block	Difference	1^{st} Block	4^{th} Block	Difference
1	Yes	16.05	18.92	2.87 ***	7.74	8.97	1.24 ***	8.30	9.94	1.65
2	Yes	15.06	17.66	2.60 **	9.02	9.49	0.47 *	6.03	8.17	2.13 *
3	No	15.98	18.28	2.30 ***	10.61	12.22	1.61 ***	5.36	6.05	0.69
4	Yes	17.88	20.38	2.50 ***	9.16	9.18	0.02	8.73	11.20	2.47 ***
5	No	13.25	15.33	2.08 ***	8.51	10.19	1.68 ***	4.76	5.14	0.38

Table B.4: Regression Analysis of Signaling Behavior

1=Signal	Low Quality Products				High Quality Products			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treament 1 (75%, $5)	-0.254	-0.255	-0.188	-0.155	0.285	0.286	0.281	0.231
	(0.315)	(0.318)	(0.318)	(0.337)	(0.361)	(0.361)	(0.362)	(0.365)
Treament 3 (25%, $5)	0.0277	0.0278	0.0775	0.0702	-0.887***	-0.889***	-0.892***	-0.928***
	(0.326)	(0.327)	(0.331)	(0.350)	(0.306)	(0.306)	(0.308)	(0.314)
Treament 4 (50%, $3)	0.233	0.234	0.346	0.377	0.603*	0.604*	0.597*	0.741**
	(0.290)	(0.291)	(0.303)	(0.319)	(0.321)	(0.322)	(0.325)	(0.346)
Treament 5 (50%, $7)	-0.715**	-0.718**	-0.725**	-0.689*	-1.374***	-1.377***	-1.378***	-1.329***
	(0.352)	(0.352)	(0.339)	(0.370)	(0.316)	(0.317)	(0.317)	(0.327)
Period		-0.0206***	-0.0211***	-0.0212***		0.0103	0.0103	0.00924
		(0.00733)	(0.00717)	(0.00705)		(0.00745)	(0.00745)	(0.00765)
Number of Safe Choices			-0.0850**	-0.0752**			0.00558	0.0129
			(0.0344)	(0.0333)			(0.0278)	(0.0294)
Age				-0.154**				-0.0207
				(0.0741)				(0.0460)
Male				0.418*				0.364
				(0.219)				(0.232)
Experienced Subjects				-0.242				0.0445
				(0.210)				(0.214)
Sophomore				1.981**				0.640
				(0.885)				(0.835)
Junior				0.354				0.308
				(0.314)				(0.325)
Senior				0.725				0.404
				(0.448)				(0.379)
Graduate Students				0.206				0.128
				(0.312)				(0.277)
GPA				0.0556				0.362***
				(0.151)				(0.131)
African American				0.0994				0.165
				(0.299)				(0.295)
Hispanic				0.599				0.151
				(0.413)				(0.436)
Asian				0.989***				0.317
				(0.379)				(0.434)
Other				-0.135				0.247
				(0.388)				(0.459)
Smoke				0.185				0.212
				(0.262)				(0.353)
Youngest Child				0.289				0.0461
				(0.304)				(0.272)
Middle Child				0.541				0.879
				(0.477)				(0.614)
Oldest Chid				0.202				0.343
				(0.274)				(0.282)
Constant	-1.600***	-1.272***	-0.393	1.761	1.343***	1.175***	1.116***	-0.256
	(0.209)	(0.235)	(0.410)	(1.552)	(0.239)	(0.272)	(0.403)	(1.083)
Observations	1,280	1,280	1,280	1,280	1,280	1,280	1,280	1,280

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.5: Regression Analysis of Bidding Behavior

Y: Bids	Non-Certified Products				Certified Products			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treament 1 (75%, $5)	-0.799***	-0.806***	-0.813***	-0.914***	1.298**	1.278**	1.212*	1.189*
	(0.277)	(0.276)	(0.272)	(0.283)	(0.641)	(0.638)	(0.645)	(0.635)
Treament 3 (25%, $5)	2.912***	2.908***	2.908***	2.790***	1.886***	1.910***	1.889***	1.940***
	(0.482)	(0.480)	(0.479)	(0.484)	(0.642)	(0.640)	(0.633)	(0.569)
Treament 4 (50%, $3)	-0.0157	-0.0184	-0.0240	-0.244	3.158***	3.180***	3.131***	3.264***
	(0.289)	(0.290)	(0.287)	(0.304)	(0.651)	(0.655)	(0.659)	(0.607)
Treament 5 (50%, $7)	0.113	0.0800	0.0788	0.0359	-1.121	-0.920	-0.898	-0.530
	(0.334)	(0.331)	(0.331)	(0.340)	(0.775)	(0.769)	(0.773)	(0.765)
Period		0.0479***	0.0479***	0.0465***		0.112***	0.112***	0.115***
		(0.00796)	(0.00796)	(0.00786)		(0.0157)	(0.0157)	(0.0159)
Number of Safe Choices			0.00764	-0.00878			0.0938	0.0914
			(0.0282)	(0.0295)			(0.0573)	(0.0569)
Age				0.0102				0.248***
				(0.0428)				(0.0777)
Male				0.0652				1.068**
				(0.264)				(0.431)
Experienced Subjects				-0.385				-0.295
				(0.251)				(0.407)
Sophomore				-0.407				-2.840*
				(0.727)				(1.503)
Junior				0.00606				-0.249
				(0.365)				(0.596)
Senior				-0.444				-1.138
				(0.420)				(0.857)
Graduate Students				0.217				-1.889***
				(0.265)				(0.603)
GPA				-0.0635				0.202
				(0.157)				(0.294)
African American				0.720**				0.302
				(0.283)				(0.529)
Hispanic				0.256				-0.244
				(0.634)				(0.954)
Asian				0.235				0.342
				(0.417)				(0.910)
Other				0.299				0.325
				(0.302)				(0.839)
Smoke				0.349				0.0819
				(0.355)				(0.605)
Youngest Child				-0.256				0.304
				(0.299)				(0.575)
Middle Child				-0.00454				1.590
				(0.437)				(0.986)
Oldest Chid				0.00619				0.0450
				(0.288)				(0.523)
Constant	9.146***	8.372***	8.288***	8.316***	16.07***	14.15***	13.11***	7.813***
	(0.250)	(0.299)	(0.462)	(1.052)	(0.431)	(0.551)	(0.818)	(2.077)
Observations	3,456	3,456	3,456	3,456	1,664	1,664	1,664	1,664
R-squared	0.172	0.194	0.194	0.214	0.090	0.136	0.141	0.191

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C. Appendix Proofs

In this appendix, I will discuss the three potential pure-strategy equilibria in the model outlined in Section 2, and derive the conditions in the propositions and corollaries. First, given the wage schedule based on employers' beliefs, define the wage difference as

$$w(1)-w(0)=(1-\mu_1)\theta_h+\mu_1\theta_l-(1-\mu_0)\theta_h-\mu_0\theta_l=(\mu_0-\mu_1)(\theta_h-\theta_l). \tag{C.1}$$

Pooling not to pursue $e_h=e_l=0$

In this case, no workers choose to pursue the degree, and all workers will be on the job market without a degree. As a result, on-equilibrium belief μ_0 will be the same as prior distribution $\mu_0=\mu$; employers will not observe any workers with the degree in the market and cannot use Bayes' rule to update μ_1, so out-of-equilibrium belief μ_1 can take any value in $[0,1]$. The wage schedule will be

$$\begin{aligned} w(0) &= (1-\mu)\ \theta_h+\mu\ \theta_l \\ w(1) &= (1-\mu_1)\ \theta_h+\mu_1\theta_l\ \in[\theta_l,\theta_h]. \end{aligned} \tag{C.2}$$

Workers' decisions to not pursue the degree will be supported by this wage schedule if

$$(1-\lambda_h)w(1)+\lambda_h w(0)-c_h\le w(0) \text{ High Type} \tag{C.3}$$

$$(1-\lambda_l)w(1)+\lambda_l w(0)-c_l\le w(0) \text{ Low Type} \tag{C.4}$$

The two incentive constraints can be rearranged as:

$$\begin{aligned} (1-\lambda_h)(w(1)-w(0)) &\le c_h \\ (1-\lambda_l)(w(1)-w(0)) &\le c_l, \end{aligned}$$

here $w(1)-w(0)=(\mu-\mu_1)(\theta_h-\theta_l)$. If $w(1)\le w(0)$ – i.e., $1\ge\mu_1\ge\mu$ – the L.H.S of both constraints is non-positive, and given that c_h and c_l are strictly positive, the constraints are satisfied; if $w(1)>w(0)$ – i.e., $\mu>\mu_1\ge 0$ –low type's constraint will be implied by the high type's. Solving the high type's constraint, we have:

$$
\begin{aligned}
w(1) - w(0) &\leq \frac{c_h}{1-\lambda_h} \\
(\mu - \mu_1)(\theta_h - \theta_l) &\leq \frac{c_h}{1-\lambda_h} \\
\mu - \mu_1 &\leq \frac{c_h}{(1-\lambda_h)(\theta_h - \theta_l)} \\
\mu_1 &\geq \mu - \frac{c_h}{(1-\lambda_h)(\theta_h - \theta_l)} \\
\mu_1 &\geq \mu - \frac{1}{\theta_h - \theta_l} \cdot \frac{c_h}{1-\lambda_h}
\end{aligned}
$$

Together with the pre-condition $\mu > \mu_1 \geq 0$, we have

$$\mu > \mu_1 \geq \mu - \frac{1}{\theta_h - \theta_l} \cdot \frac{c_h}{1-\lambda_h}$$

Combining with the case $1 \geq \mu_1 > \mu$, the range of supporting out-of-equilibrium beliefs is

$$1 > \mu_1 \geq \mu - \frac{1}{\theta_h - \theta_l} \cdot \frac{c_h}{1-\lambda_h}$$

Consider the cases in which the low type's constraint $(1-\lambda_l)(w(1) - w(0)) \leq c_l$ is always satisfied no matter what μ_1 is. That is, for any $\mu_1 \in [0,1]$ we should have

$$
\begin{aligned}
w(1) - w(0) &\leq \frac{c_l}{1-\lambda_l} \\
(\mu - \mu_1)(\theta_h - \theta_l) &\leq \frac{c_l}{1-\lambda_l} \\
\mu - \mu_1 &\leq \frac{c_l}{(1-\lambda_l)(\theta_h - \theta_l)} \\
\mu_1 &\geq \mu - \frac{c_l}{(1-\lambda_l)(\theta_h - \theta_l)}, \quad \forall \mu_1 \in [0,1] \\
0 &\geq \mu - \frac{c_l}{(1-\lambda_l)(\theta_h - \theta_l)} \\
\frac{c_l}{\theta_h - \theta_l} &\geq \mu(1-\lambda_l)
\end{aligned}
$$

Therefore, if $\frac{c_l}{\theta_h - \theta_l} \geq \mu(1-\lambda_l)$, deviating to $e_l = 1$ is never profitable for the low type no matter how favorable the employer's out-of-equilibrium belief is. At the same time, if $\frac{c_h}{\theta_h - \theta_l} < \mu(1-\lambda_h)$, then deviating to $e_h = 1$ is profitable for the high-type worker under some favorable belief of employer $[0, \mu - \frac{c}{(1-\lambda_h)(\theta_h - \theta_l)}]$. So, by the Cho-Kreps intuitive criterion, the employer's out-of-equilibrium belief should be updated to $\mu_1 = 0$, and he will offer a wage of θ_h, which will attract the high-type worker away and disturb this pooling equilibrium.

Separating $e_h = 1$ and $e_l = 0$

In this case, the high-type workers will pursue the degree while the low type will not. As a result, employers are able to verify productivities for workers with and without the degree and to update their beliefs using Bayes rule:

$$\mu_0 = \frac{\mu}{\mu + \lambda_h(1-\mu)}, \quad \mu_1 = 0$$

Given the updated belief, the wage schedule will be

$$w(0) = \tfrac{\lambda_h(1-\mu)}{\mu+\lambda_h(1-\mu)} \cdot \theta_h + \tfrac{\mu}{\mu+\lambda_h(1-\mu)} \cdot \theta_l, \quad w(1) = \theta_h \tag{C.5}$$

And for the market to be in equilibrium, the wage schedule will need to sustain workers' choices:

$$(1-\lambda_h)w(1) + \lambda_h w(0) - c_h \geq w(0) \text{ High Type} \tag{C.6}$$

$$(1-\lambda_l)w(1) + \lambda_l w(0) - c_l \leq w(0) \text{ Low Type} \tag{C.7}$$

Rearrange the incentive constraints as:

$$(1-\lambda_h)(w(1) - w(0)) \geq c_h \qquad \text{High Type}$$

$$(1-\lambda_l)(w(1) - w(0)) \leq c_l, \qquad \text{Low Type}$$

Where $w(1) - w(0) = \mu_0(\theta_h - \theta_l) = \frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h - \theta_l)$. Further simplifying the constraints, we have:

$$\frac{c_h}{1-\lambda_h} \leq w(1) - w(0) \leq \frac{c_l}{1-\lambda_l}$$

$$\frac{c_h}{1-\lambda_h} \leq \frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h - \theta_l) \leq \frac{c_l}{1-\lambda_l}$$

So separating equilibrium exists if and only if the parameters satisfy

$$\frac{c_h}{1-\lambda_h} \leq \frac{\mu}{\mu+\lambda_h(1-\mu)}(\theta_h - \theta_l) \leq \frac{c_l}{1-\lambda_l}$$

Pooling to pursue $e_h = e_l = 1$

Finally, consider the case in which both types choose to pursue the degree. Although both types of workers choose to pursue the degree, due to a positive failure rate, the employer will still observe $D = 0$ and will be able to update his belief μ_0. In this situation, the employer's beliefs given observing $D = 1$ and $D = 0$ are

$$\mu_1 = \frac{(1-\lambda_l)\mu}{(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)}, \quad \mu_0 = \frac{\lambda_l \mu}{\lambda_l \mu + \lambda_h(1-\mu)}$$

Given the beliefs, the wage schedule will be

$$w(e) = \begin{cases} (1-\mu_0)\theta_h + \mu_0\theta_l, & e = 0 \\ (1-\mu_1)\theta_h + \mu_1\theta_l, & e = 1 \end{cases} \tag{C.8}$$

Note that since we have $\lambda_h < \lambda_l$, it is always the case that $\mu_0 > \mu_1$, as shown below, so $w(1) - w(0) = (\mu_0 - \mu_1)(\theta_h - \theta_l) > 0$.

$$\begin{aligned} \mu_0 - \mu_1 &= \frac{\lambda_l \mu}{\lambda_l \mu + \lambda_h(1-\mu)} - \frac{(1-\lambda_l)\mu}{(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)} \\ &= \frac{\lambda_l \mu[(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)] - (1-\lambda_l)\mu[\lambda_l \mu + \lambda_h(1-\mu)]}{[(1-\lambda_l)\mu + (1-\lambda_h))(1-\mu)][(\lambda_l \mu + \lambda_h(1-\mu))]} \\ &= \frac{\lambda_l \mu[(1-\lambda_h)(1-\mu)] - (1-\lambda_l)\mu[\lambda_h(1-\mu)]}{[(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)][(\lambda_l \mu + \lambda_h(1-\mu))]} \\ &= \frac{\mu(1-\mu)[\lambda_l(1-\lambda_h) - (1-\lambda_l)\lambda_h]}{[(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)][(\lambda_l \mu + \lambda_h(1-\mu))]} \\ &= \frac{\mu(1-\mu)(\lambda_l - \lambda_h)}{[(1-\lambda_l)\mu + (1-\lambda_h)(1-\mu)][\lambda_l \mu + \lambda_h(1-\mu)]} > 0 \end{aligned}$$

Workers' incentive constraints can be rearranged as:

$$(1-\lambda_h)(w(1) - w(0)) \geq c_h \ \text{ High Type} \tag{C.9}$$

$$(1-\lambda_l)(w(1) - w(0)) \geq c_l \ \text{ Low Type} \tag{C.10}$$

where $w(1)-w(0)=(\mu_0-\mu_1)(\theta_h-\theta_l)>0$. Since we also have $\lambda_h<\lambda_l$ and $c_h<c_l$, the high type's constraint is implied by the low type's:

$$\begin{aligned}(1-\lambda_l)(w(1)-w(0)) &\geq c_l\\ (1-\lambda_l)(\mu_0-\mu_1)(\theta_h-\theta_l) &\geq c_l\\ (\mu_0-\mu_1)(\theta_h-\theta_l) &\geq \frac{c_l}{1-\lambda_l}\end{aligned}$$

When this inequality is not satisfied, pooling at $e=1$ can be avoided; that is:

$$\begin{aligned}&\frac{c_l}{1-\lambda_l}\geq(\mu_0-\mu_1)(\theta_h-\theta_l)\\ &\text{where } \mu_1=\frac{(1-\lambda_l)\mu}{(1-\lambda_l)\mu+(1-\lambda_h)(1-\mu)},\quad \mu_0=\frac{\lambda_l\mu}{\lambda_l\mu+\lambda_h(1-\mu)}\end{aligned}$$

Comparing this condition with the condition on $\frac{c_l}{1-\lambda_l}$ for existence of a separating equilibrium, we have

$$\mu_0-\mu_1\leq\mu_0=\frac{\mu}{\mu+\frac{\lambda_h}{\lambda_l}(1-\mu)}\leq\frac{\mu}{\mu+\lambda_h(1-\mu)}$$

Since $\lambda_l<1$, we have $\frac{\lambda_h}{\lambda_l}>\lambda_h$. This means that, when the separating strategy $e_h=1,e_l=0$ is an equilibrium strategy, pooling to pursue cannot be an equilibrium.

The last case is the most wasteful; to show this, denote the beliefs in this pooling equilibrium μ_0^{Pool} and μ_1^{Pool}. Educational attainment, in this pooling equilibrium, can act as a weak signal of a worker's type since we have $\mu_0^{Pool}>\mu>\mu_1^{Pool}$; that is, the degree status is negatively correlated with a worker's likelihood to be the low type. However, recall that in the separating equilibrium, the negative relationship is stronger, and, therefore, a degree is a stronger signal since

$$\mu_0^{Sep}=\frac{\mu}{\mu+\lambda_h(1-\mu)}>\mu_0^{Pool},\quad \mu_1^{Sep}=0<\mu_1^{Pool}$$

For given c_h and c_l, we conclude that pooling to pursue is less efficient than the separating equilibrium, since everyone incurs the cost, but the degree does not convey as much information.[41]. The inefficient pooling equilibrium can be *avoided* by raising the low type's dropout risk.

[41] An implicit assumption in this argument is such information is socially valuable. The social value could be the technological innovations in the long run as a result of better match between workers' abilities and job types. Plus, when discharge of an employee is costly and the employers are risk averse, the elimination of employer's uncertainty on worker's type will promote hiring in the labor market.

Sequential Equilibrium

Perfect Bayesian Equilibrium only requires the existence of supporting off-the-equilibrium belief. Sequential equilibrium additionally requires the supporting off-the- equilibrium belief to be consistent in the following sense: there *exists* a tremble in worker's strategy so that the off-the-equilibrium beliefs can be reached and updated with Bayes rule, and when the tremble goes to zero, the limit of the off-the-equilibrium beliefs need to converge to the supporting beliefs. Since in the separating equilibrium, both information sets of employers are reached, so the separating equilibrium is sequential equilibrium. Now check the consistency of the supporting off-the-equilibrium for the pooling PBE in which $e_h = e_l = 0$.

Let the high type choose $e_h = 1$ with probability ε^2, and the low type with ε. Then the off-the-equilibrium belief μ_1 can be updated as

$$\mu_1 = \frac{\mu\varepsilon(1-\lambda_l)}{\mu\varepsilon(1-\lambda_l)+(1-\mu)\varepsilon^2(1-\lambda_h)}$$

When ε goes to zero, μ_1 goes to 1, which is one of the off-the-equilibrium beliefs that supports the pooling strategy of workers. Hence, the pooling PBE is also a sequential equilibrium of this market.

D. INSTRUCTIONS FOR THE EXPERIMENTS

Instructions for Part I

Welcome and thank you for participating in this experiment. The experiment has 2 parts; this is the instruction for Part I. Please read the instructions carefully to help you understand the task and earn more money.

In this part, you will trade products in series of markets. In each market, three people will interact with each other: ***one person*** plays as the seller who is selling ***one*** product, and ***the other two people*** will be the buyers who are bidding for this product. The buyer who submits the higher bid will win the product; if the bids are equal, then one buyer will be randomly selected as the winner. A deal will be made between the seller and the winning buyer, at a price equal to the winning bid.

You will trade with other participants for 32 market periods in Part I; you will then proceed to Part II to make some more money before we conclude this experiment and pay your earnings. Instructions for Part II will be given after Part I is completed.

Groups and Roles

All participants will be *randomly* divided into small groups of 3 people in *each* period; each small group forms a market. One unit of product will be traded *within* each market; **you will only trade with the 2 partners in your own group.** The random grouping procedure will be performed before each period, so keep in mind that **you will NOT trade with the same partners in two different periods.** *IDs of group members will not be disclosed at any time.*

Each participant gets to play buyer in some periods, and seller in the other periods. Throughout these 32 periods, your role will change back and forth; generally, you will play consecutively as one role for a few periods before switching to the other. You'll find out your role as soon as a trading period begins; it will also be highlighted at the top section of your computer screen throughout that period.

Trading in a Market

There are two types of products with high or low quality; each high quality product has a value of $25, and each low quality product has a value of $10. After groups are formed, each seller will get one product to sell. *1/2* of the sellers will get the high quality products; *1/2* sellers will get the low quality ones. **The seller will be informed of the quality of the product she gets as soon as a period begins; the 2 buyers will NOT be informed of the quality of the product UNTIL the end of each period.**

The seller will then decide if she wants to spend $5 to take a quality test on her product: there is 90% chance for the high quality product to pass the test; 10% chance for the low quality product to pass. **Upon passing the test, a quality certificate will be issued to the product.** Notice that the $5 will be deducted from seller's profit if she decides to take the test, no matter if the product passes or fails.

Then the product will be placed on the market, and each buyer will need to submit a bid. The buyer with the higher bid wins the product. The buyers can submit the bid in the range of $0 to $30, in multiples of $0.25. **Before submitting their bids, the buyers will be informed if the product comes with a certificate, but NOT the seller's decision.** After both buyers submit the bids, they will be informed of the winner as well as the quality of the product in their market in that period**.**

The product will be sold to the winner at a price equal to his bid. Seller's profit is equal to this price (that is, the winning bid); ***minus*** the $5 cost of test if the seller decided to take the test. The winner of the product will get the product value ($25 or $10, depending on the product that he wins) ***minus*** his bid. ***In addition***, both buyers (that is, also the buyer who did not win the product) receives $8 in every period. Everyone will be informed of their earnings in the current periods before moving on to next period.

The profit of everyone in the market of each period is also shown in the following table:

Buyer with lower Bid	$8
Buyer with higher Bid	**$25** – Bid +$8 if the buyer wins a high quality product **$10** – Bid +$8 if the buyer wins a low quality product
Seller	Product Price – $5 if she took the test Product Price if she *didn't* take the test

The Quality Test

If you are a seller and decide to take the test, you will see a bar with a success region, a failure region and a randomly moving needle. The region of success is 90% of the bar if your product has high quality (Figure 1); the region of success is 10% of the bar if your product has low quality (Figure 2). The needle is equally likely to appear at any position along the bar, and it will stop moving after 5 seconds. If the needle ends up in the success region, your product passes the test and will get a quality certificate; if it ends up in the failure region, your product fails the test and will be placed on the market without a quality certificate.

Figure 1 High Quality Product Test

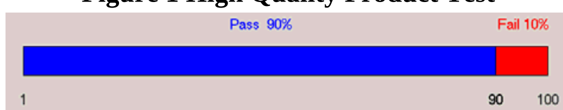
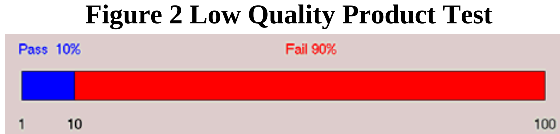


Figure 2 Low Quality Product Test



Summary: a trading period proceeds as follows

⇒ Markets are formed randomly
⇒ Products are distributed to sellers randomly

Then within each market:

⇒ Seller learns the value of her product
⇒ Seller decides whether to take the test
⇒ Product is placed on the market, with or without a quality certificate
⇒ Buyers make bids
⇒ Buyers learn the quality of the product in their market; Seller and buyers learn results and profits

Payment

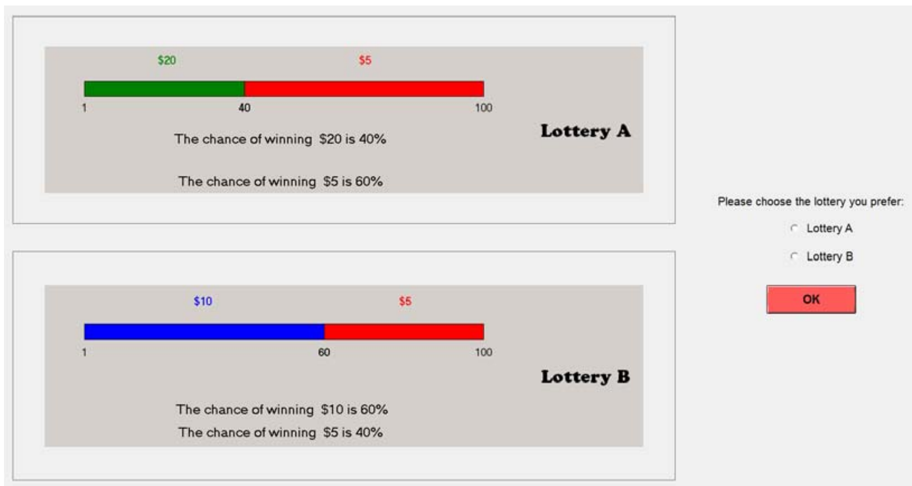
After Part I is completed, one of these 32 market periods will be randomly chosen by drawing a numbered ball from the bingo cage, and your payoff in the chosen period will be your earnings from Part I. Since you don't know which period will be chosen, please decide carefully in every period.

Instructions for Part II

In this part of the experiment, you will see pairs of lotteries. Your task is to choose which lottery you prefer to play in each pair. ***After you make each choice, the lottery of your choice will be played out to determine your payoff in that task. There is no right or wrong answer, simply pick the one you prefer to play.***

Each lottery will offer monetary prizes with some probabilities. Different lotteries might differ in prizes and probabilities. You will see one pair of lotteries at a time, and here is an example of what you will see on your computer screen:

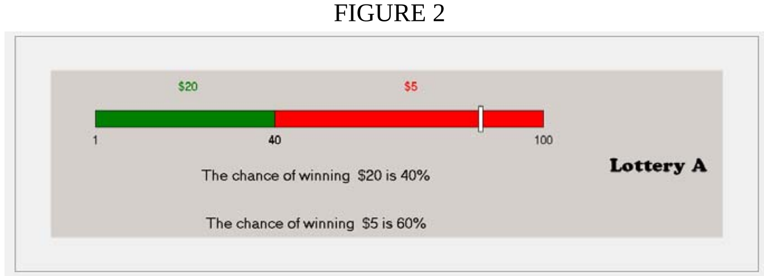
FIGURE 1



You can tell the chances of winning each prize from the length of same-colored bar and the descriptions below the bar. In Figure 1, **Lottery A** offers $20 with 40% chance, so length of green bar is 40% of the whole bar; it offers $5 with 60% chance, so the red bar is 60% length of the whole bar. **Lottery B** offers a prize of $10 with a 60% chance, so the length of the blue bar is 60% length of the whole bar; it offers a prize of $5 with a 40% chance, so the length of the red bar is the other 40% length of the whole bar. Notice that different lotteries might have these colors matched to different prizes, for example if a lottery involves prizes $20, $15 and $5, they will also be shown in green, blue, red, respectively.

You can choose your preferred lottery by clicking on the corresponding button on the right. After you click OK, you will see your chosen lottery on the screen and a white needle will show up. The needle is equally likely to appear at any position along the bar, and it will stop moving after 5 seconds. The position of the needle ends up in will be the prize you win, and it will be your payoff of this lottery task. For example, if you have chosen Lottery A and the needle in Figure 2 stopped in the red region with $5 on top of it, so the payoff is $5.

FIGURE 2



After you make all 20 choices, 20 balls numbered 1 to 20 will be put in the bingo cage; a numbered ball will be randomly drawn, and your payoff in that lottery task will be your earnings in this part. ***Please choose carefully in each task, as you don't know which task will be chosen until after all 20 decisions are made.***

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Figure 1: Signaling Rates of Each Seller in Each Treatment (by Quality Type)

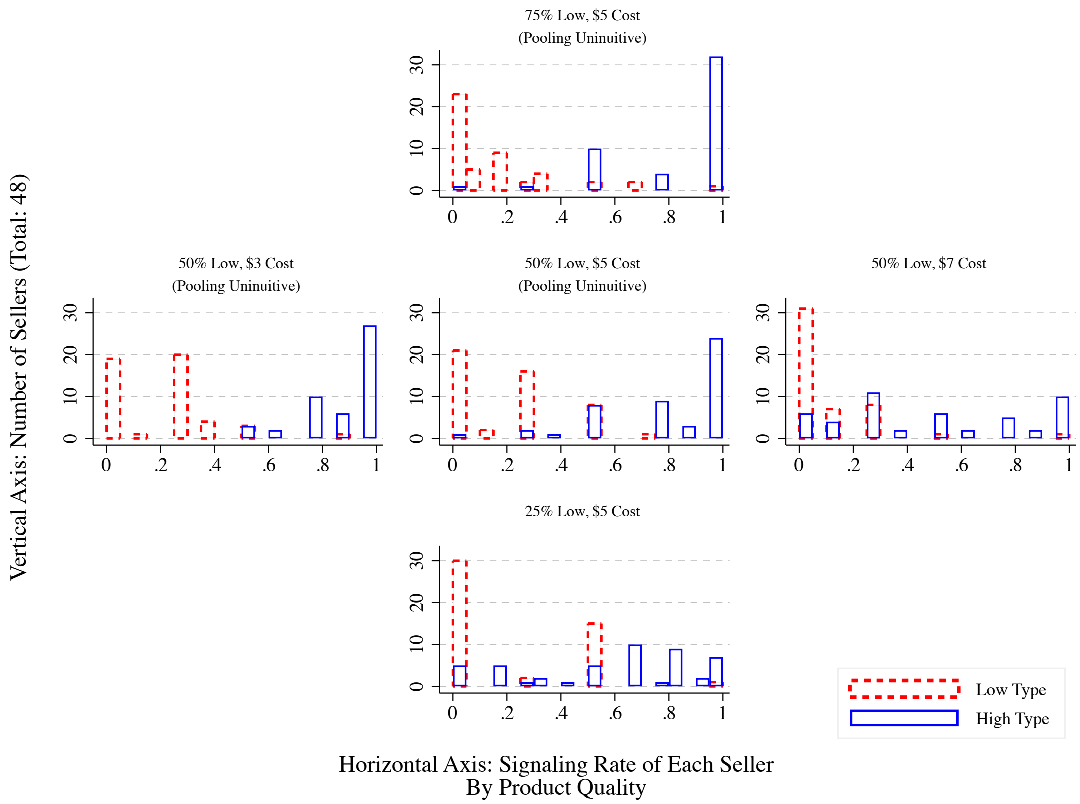


Figure 2: Average Signaling Rate in Each Treatment (by Quality Type)

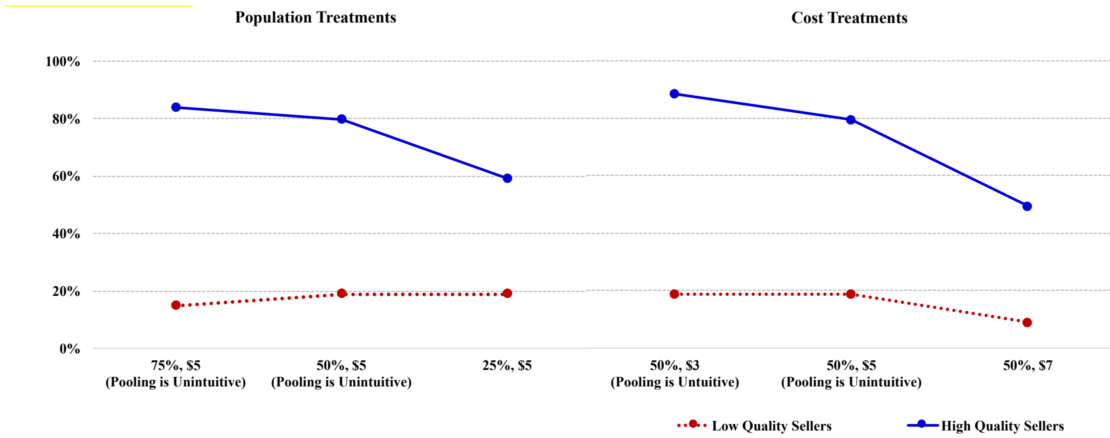
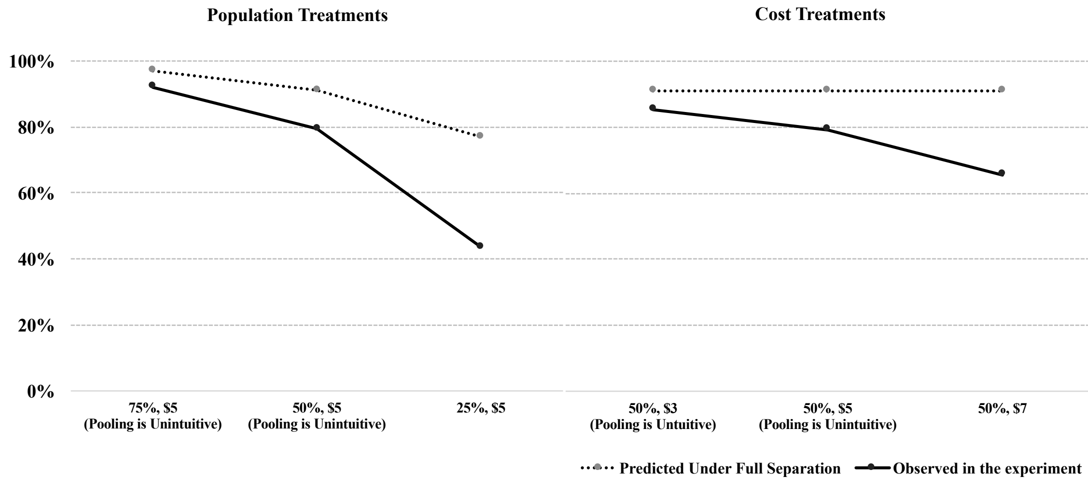


Figure 3: Share of Low-Quality Products Among Non-Certified Products



[1] The dashed line is the predicted share of low-quality products among non-certified products, if all sellers with high-quality products take the test and all sellers with low-quality products do not.
[2] The solid line is the observed share of low-quality products among non-certified products in each treatment.

Figure 4: Average Bids per Buyer in Each Treatment (by Certification Status)

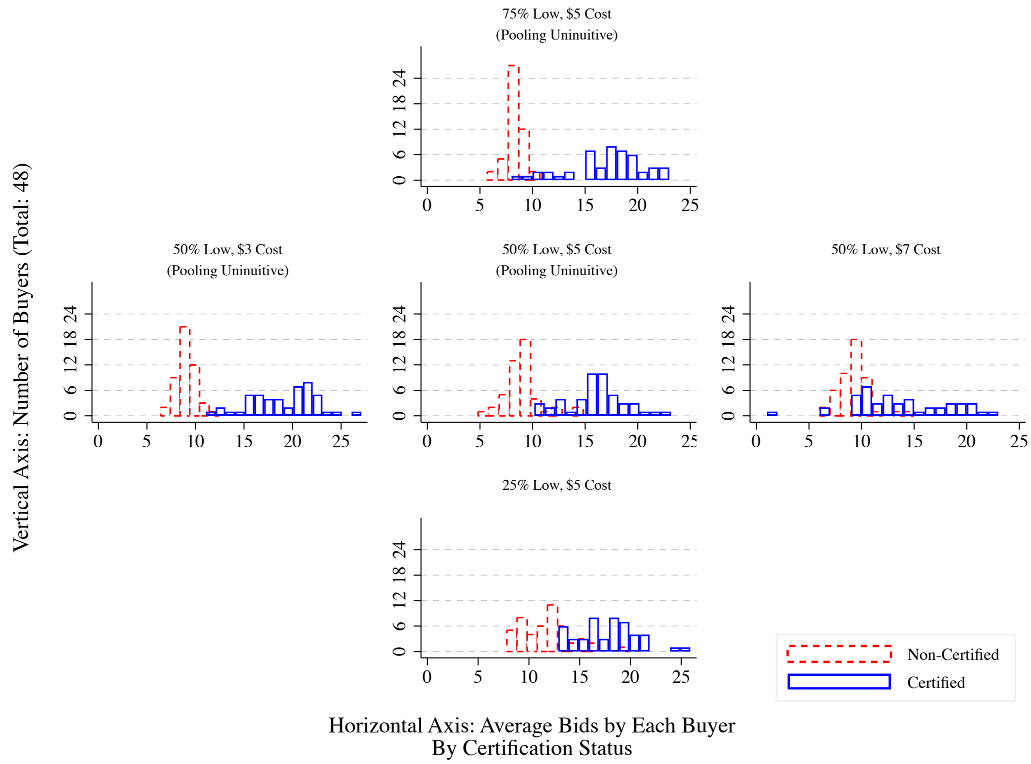
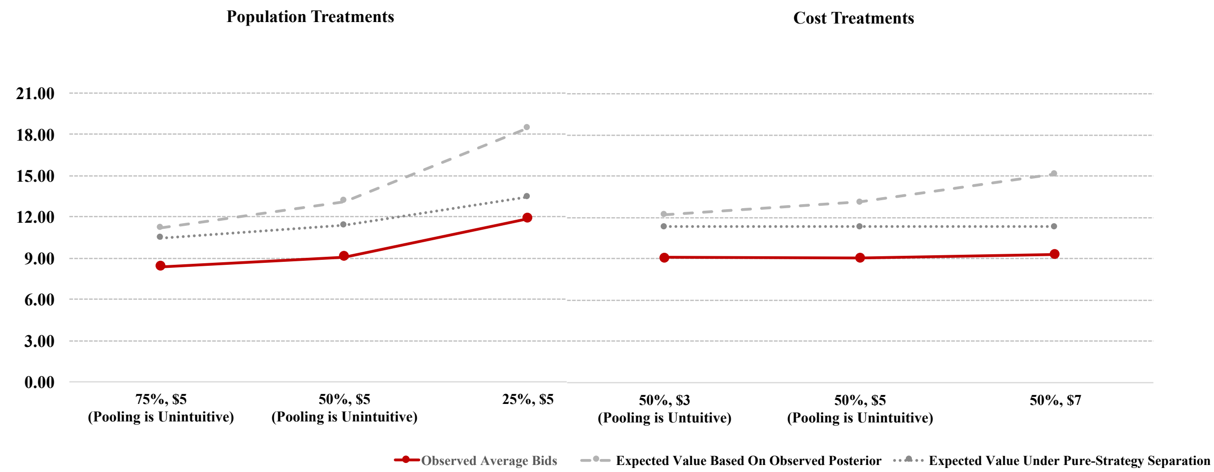


Figure 5: Mean Bids on Non-Certified Products in Each Treatment



[1] The dashed gray line is the expected value of non-certified products based on the observed posterior in the experiments.
[2] The dotted gray line is the expected value of non-certified products based on the posterior when the market in pure-strategy separating equilibrium;], that is, when high types always signal and low types never signals.
[3] The solid red line is the mean of average bids on non-certified products observed in the experiments.

Table 1: Parameterization in Each Treatment

Treatment	Low Type	Education Cost	Productivity		Dropout Risk		Is Equilibrium?	
			High Type	Low Type	High Type	Low Type	Separating	Pooling[1]
1	***75%***	$5	$25	$10	10%	90%	Yes	Yes but Unintuitive
2	***50%***	$5	$25	$10	10%	90%	Yes	Yes but Unintuitive
3	***25%***	$5	$25	$10	10%	90%	Yes	Yes
4	50%	***$3***	$25	$10	10%	90%	Yes	Yes but Unintuitive
2	50%	***$5***	$25	$10	10%	90%	Yes	Yes but Unintuitive
5	50%	***$7***	$25	$10	10%	90%	Yes	Yes

[1] Pooling to pursue is not an equilibrium in any of these treatments, so in the current table, as well as in the following discussion, pooling is referring to "pooling not to pursue".

Table 2: Cho-Kreps Intuitive Refinement of Pooling Equilibrium

Treatment		**Population Treatments**			**Cost Treatments**		
		75%, \$5	50%, \$5	25%, \$5	50%, \$3	50%, \$5	75%, \$7
Pooling Wage		13.75	17.5	21.25	17.5	17.5	17.5
Expected Payoff if Deviate (Highest Possible[1])	**High Type**	18.875	19.25	19.625	21.25	19.25	17.25
	Low Type	9.875	13.25	16.625	15.25	13.25	11.25
Pooling at Not Pursuing		Unintitive	Unintuitve	Intuitive	Unintuitve	Unintuitve	Intuitive

[1] The highest possible expected payoff is calculated under the most favorable wage offer for degree holders; that is, employers offer \$25 to workers who have a degree.

Table 3: Role Assignment in Each Session

	Periods			
Subject ID [1]	1 - 8	9 - 16	17 - 24	25 - 32
1 - 8	*Seller*	Buyer	Buyer	Seller
9 - 16	Buyer	*Seller*	Buyer	Buyer
17 - 24	Buyer	Buyer	*Seller*	*Buyer*

[1] Subject ID was randomly assigned at the beginning of each sesion, so subjects with adjacent IDs do not necessarily take adjacent seats.
[2] Subjects were merely informed that their roles would switch back and forth over the 32 periods, but were not told the specifics of the block design or the role switching rules.

Table 4: Payoff in Each Period of Treatment 2

Buyer with lower Bid	\$8	
Buyer with higher Bid	\$25 − Bid +\$8	if the product has high quality
	\$10 − Bid +\$8	if the product has low quality
Seller	Product Price − \$5	if she took the test
	Product Price	if she *didn't* take the test

[1] \$8 is paid to all buyers as a non-salient endowment. The purpose is to cover possible losses from overbidding.

Table 5: Summaries of Signaling and Bidding Behavior in Each Session

Treatment[1]	Cost	Share of Low Type[4] (%)			Share of Certified Products[6] (%)	Signaling Rate[2] (%)			Average Bidding[3] ($)			Average Price[5] ($)		
		All μ	Certified μ_1	Non-Certified μ_0		High Type S_H	Low Type S_L	Difference S_{DIFF}	Certified B_C	Non-Certified B_{NC}	Difference B_{DIFF}	Certified	Non-Certified	Difference
1	$5	75	4.9	92.0	19.3	83.9	14.8	69.1	16.99	8.36	8.63	19.47	9.04	10.42
2	$5	50	1.5	79.3	37.1	79.7	18.8	60.9	16.02	9.06	6.96	18.00	10.35	7.65
3	$5	25	0.6	43.6	40.9	59.2	18.8	40.5	17.74	11.86	5.88	19.74	13.92	5.86
4	$3	50	2.7	85.3	42.2	88.5	18.8	69.8	19.07	9.08	9.99	21.34	10.09	11.25
2	$5	50	1.5	79.3	37.1	79.7	18.8	60.9	16.02	9.06	6.96	18.00	10.35	7.65
5	$7	50	2.0	65.5	22.8	49.5	9.1	40.4	13.68	9.32	4.35	15.88	10.51	5.28

1 In treatments 1, 2 and 4, pooling is unintuitive and separating is the only intuitive equilibrium; in treatments 3 and 5, pooling is intuitive and cannot be refined by Cho-Kreps Intuitive Criterion. For easy comparison, Treatment 2 is listed two times in the table.
2 Empirical distributions of S_H, S_L and S_{DIFF} in each treatment can be found in Figure 1 and Figure A.2.
3 Empirical distributions of B_C, B_{NC} and B_{DIFF} in each treatment can be found in Figure 4 and Figure A.3.
4 For each buyer, μ_0 is the share of low quality products among non-certified products he traded, and μ_1 is the share of low quality products among certified products. Empirical distributions of μ_0 and μ_1 can can be found in Figure A.4
5 These columns report the average prices each seller receives when their products are certified or not certified.
6 This column reports how often each buyer encounters a certified product, out of all the products they traded as buyers.

Table 6: Price Premium and Seller Decision in Each Treatment

Treatment	Cost	Share of Low Type	Average Price ($)			Expected Payoff of High Type ($)			Signaling Rate Among High Type S_H	Expected Payoff of Low Type ($)			Signaling Rate Among Low Type S_L
			Certified	Non-Certified	Difference	Send Sigal	Not Send Signal	Difference		Send Sigal	Not Send Signal	Difference	
1	$5	75%	19.47	9.04	10.42	13.43	9.04	4.38	83.9%	5.08	9.04	-3.96	14.8%
2	$5	50%	18.00	10.35	7.65	12.24	10.35	1.89	79.7%	6.12	10.35	-4.23	18.8%
3	$5	25%	19.74	13.92	5.86	14.16	13.92	0.24	59.2%	9.51	13.92	-4.42	18.8%
4	$3	50%	21.34	10.09	11.25	17.21	10.09	7.12	88.5%	8.22	10.09	-1.88	18.8%
2	$5	50%	18.00	10.35	7.65	12.24	10.35	1.89	79.7%	6.12	10.35	-4.23	18.8%
5	$7	50%	15.88	10.51	5.28	8.34	10.51	-2.17	49.5%	4.04	10.51	-6.46	9.1%

Table 7: Self-Correlation Between Subjects' Signaling and Bidding Strategies

Low Type	Cost	$B_{DIFF} \times S_{DIFF}$	$B_{NC} \times S_{DIFF}$	$B_{C} \times S_{DIFF}$
75%	$5	0.093	-0.058	0.080
50%	$5	0.269 *	-0.042	0.245 *
25%	$5	0.485 *	-0.408 *	0.313 *
50%	***$3***	0.346 *	-0.089	0.334 *
50%	***$7***	0.571 *	0.130	0.564 *

* Significant at 10% level

Table 8: Panel Regression on Individual Signaling Behavior by Treatment

1=Signal	Population Treatments								
	75% Low	50% Low	25% Low	75% Low	50% Low	25% Low	75% Low	50% Low	25% Low
High	4.283***	3.296***	2.579***	3.078***	2.337***	2.018***	3.008***	2.348***	2.021***
	(0.383)	(0.276)	(0.305)	(0.608)	(0.479)	(0.556)	(0.603)	(0.479)	(0.556)
Period				-0.0245	-0.0248	-0.0353	-0.0240	-0.0245	-0.0353
				(0.0194)	(0.0200)	(0.0279)	(0.0190)	(0.0199)	(0.0279)
High x Period				0.0822**	0.0624**	0.0358	0.0835**	0.0621**	0.0358
				(0.0354)	(0.0268)	(0.0307)	(0.0353)	(0.0268)	(0.0307)
Number of Safe Choices							-0.144***	-0.0792*	-0.0389
							(0.0538)	(0.0450)	(0.0610)
Constant	-2.223***	-1.745***	-2.060***	-1.850***	-1.368***	-1.507***	-0.162	-0.527	-1.074
	(0.263)	(0.219)	(0.335)	(0.393)	(0.378)	(0.534)	(0.713)	(0.595)	(0.859)
1=Signal	Cost Treatments								
	$3	$5	$7	$3	$5	$7	$3	$5	$7
High	3.463***	3.296***	2.849***	2.438***	2.337***	2.497***	2.430***	2.348***	2.496***
	(0.274)	(0.276)	(0.311)	(0.483)	(0.479)	(0.551)	(0.483)	(0.479)	(0.551)
Period				-0.0107	-0.0248	-0.0528*	-0.0109	-0.0245	-0.0528*
				(0.0172)	(0.0200)	(0.0279)	(0.0171)	(0.0199)	(0.0279)
High x Period				0.0686**	0.0624**	0.0269	0.0690**	0.0621**	0.0270
				(0.0282)	(0.0268)	(0.0318)	(0.0282)	(0.0268)	(0.0318)
Number of Safe Choices							0.0378	-0.0792*	0.0133
							(0.0397)	(0.0450)	(0.0549)
Constant	-1.438***	-1.745***	-2.876***	-1.270***	-1.368***	-2.093***	-1.713***	-0.527	-2.237***
	(0.181)	(0.219)	(0.333)	(0.330)	(0.378)	(0.500)	(0.576)	(0.595)	(0.780)

For each regression: Number of Observations 512, Number of Subjects 48
Robust Standard errors in parentheses, errors clustered at the subject level.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 9: Regression Analysis on Signaling Behavior

1=Signal	Low Quality Products			High Quality Products		
	(1)	(2)	(3)	(5)	(6)	(7)
Treament 1 (75%, $5)	-0.254	-0.255	-0.188	0.285	0.286	0.281
	(0.315)	(0.318)	(0.318)	(0.361)	(0.361)	(0.362)
Treament 3 (25%, $5)	0.0277	0.0278	0.0775	-0.887***	-0.889***	-0.892***
	(0.326)	(0.327)	(0.331)	(0.306)	(0.306)	(0.308)
Treament 4 (50%, $3)	0.233	0.234	0.346	0.603*	0.604*	0.597*
	(0.290)	(0.291)	(0.303)	(0.321)	(0.322)	(0.325)
Treament 5 (50%, $7)	-0.715**	-0.718**	-0.725**	-1.374***	-1.377***	-1.378***
	(0.352)	(0.352)	(0.339)	(0.316)	(0.317)	(0.317)
Period		-0.0206***	-0.0211***		0.0103	0.0103
		(0.00733)	(0.00717)		(0.00745)	(0.00745)
Number of Safe Choices			-0.0850**			0.00558
			(0.0344)			(0.0278)
Constant	-1.600***	-1.272***	-0.393	1.343***	1.175***	1.116***
	(0.209)	(0.235)	(0.410)	(0.239)	(0.272)	(0.403)

For each regression: Number of Observations: 1280

Robust standard errors in parentheses

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

Table 10: Panel Regression on Individual Bidding Behavior by Treatment

Bids	**Population Treatments**								
	75% Low	50% Low	25% Low	75% Low	50% Low	25% Low	75% Low	50% Low	25% Low
Certified	8.962***	6.979***	5.973***	8.195***	4.958***	5.387***	8.195***	4.960***	5.389***
	(0.477)	(0.431)	(0.607)	(0.941)	(0.923)	(0.845)	(0.941)	(0.924)	(0.845)
Period				0.0483***	0.0304	0.0773***	0.0483***	0.0304	0.0777***
				(0.0125)	(0.0238)	(0.0213)	(0.0125)	(0.0239)	(0.0213)
Certified x Period				0.0418	0.116***	0.0320	0.0418	0.116***	0.0310
				(0.0343)	(0.0436)	(0.0332)	(0.0343)	(0.0436)	(0.0333)
Number of Safe Choices							0.0128	0.0175	0.166**
							(0.0374)	(0.0608)	(0.0733)
Constant	8.355***	9.064***	12.05***	7.566***	8.579***	10.79***	7.416***	8.389***	8.945***
	(0.118)	(0.252)	(0.384)	(0.286)	(0.520)	(0.528)	(0.465)	(0.953)	(1.027)
Bids	**Cost Treatments**								
	$3	$5	$7	$3	$5	$7	$3	$5	$7
Certified	10.05***	6.979***	5.232***	8.184***	4.958***	5.047***	8.180***	4.960***	5.046***
	(0.535)	(0.431)	(0.613)	(0.865)	(0.923)	(0.776)	(0.867)	(0.924)	(0.776)
Period				-0.00455	0.0304	0.0748***	-0.00460	0.0304	0.0748***
				(0.0115)	(0.0238)	(0.0153)	(0.0115)	(0.0239)	(0.0153)
Certified x Period				0.110***	0.116***	0.0204	0.111***	0.116***	0.0203
				(0.0370)	(0.0436)	(0.0302)	(0.0370)	(0.0436)	(0.0302)
Number of Safe Choices							0.0273	0.0175	-0.0378
							(0.0582)	(0.0608)	(0.0602)
Constant	9.130***	9.064***	9.361***	9.208***	8.579***	8.098***	8.889***	8.389***	8.512***
	(0.158)	(0.252)	(0.220)	(0.291)	(0.520)	(0.363)	(0.789)	(0.953)	(0.798)

For each regression: Number of Observations 1024, Number of Subjects 48
Robust Standard errors in parentheses, errors clustered at the subject level.
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 11: Regression Analysis on Bidding Behavior

Bids	Non-Certified Products			Certified Products		
	(1)	(2)	(3)	(4)	(5)	(6)
Treament 1 (75%, $5)	-0.799***	-0.806***	-0.813***	1.298**	1.278**	1.212*
	(0.277)	(0.276)	(0.272)	(0.641)	(0.638)	(0.645)
Treament 3 (25%, $5)	2.912***	2.908***	2.908***	1.886***	1.910***	1.889***
	(0.482)	(0.480)	(0.479)	(0.642)	(0.640)	(0.633)
Treament 4 (50%, $3)	-0.0157	-0.0184	-0.0240	3.158***	3.180***	3.131***
	(0.289)	(0.290)	(0.287)	(0.651)	(0.655)	(0.659)
Treament 5 (50%, $7)	0.113	0.0800	0.0788	-1.121	-0.920	-0.898
	(0.334)	(0.331)	(0.331)	(0.775)	(0.769)	(0.773)
Period		0.0479***	0.0479***		0.112***	0.112***
		(0.00796)	(0.00796)		(0.0157)	(0.0157)
Number of Safe Choices			0.00764			0.0938
			(0.0282)			(0.0573)
Constant	9.146***	8.372***	8.288***	16.07***	14.15***	13.11***
	(0.250)	(0.299)	(0.462)	(0.431)	(0.551)	(0.818)
Observations	3,456	3,456	3,456	1,664	1,664	1,664
R-squared	0.172	0.194	0.194	0.090	0.136	0.141