The Winner's Curse in a Takeover Game with Two-Sided Asymmetric Information: Theory and Experiments

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Abstract

This paper studies how *cursedness*—the tendency to neglect how other people's strategies depend on their private information—affects trade in a takeover game with one buyer and seller. I apply the Cursed Sequential Equilibrium concept, showing that information transmission and allocative efficiency depend on the degree of information asymmetry and size of the stakes. Finally, this paper discusses two experiments to test the model predictions and explore whether experience in different roles impacts cursed behavior.

JEL Classification Numbers: C72, D82, D9

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1 Introduction

People often make decisions under incomplete information in many high-stakes economic and political settings, including in markets for real estate, telecommunications, online advertising, and labor. To predict equilibrium behavior, standard game theory assumes that people are Bayesians who can figure out how other people are likely to behave. In fact, empirical evidence, both in the field and lab, suggests that people find it challenging to perform Bayesian inference correctly.

One explanation for this widely observed phenomenon is the "winner's curse" or "cursedness", which describes a person's tendency to neglect the correlation between other people's strategies and private information (Bazerman and Samuelson, 1983; Thaler, 1988; Kagel and Levin, 1986; Hendricks et al., 2003). For instance, in a two-person trade game, a buyer who bids for an asset of unknown value should realize that if their bid is accepted, it means that their bid exceeds the seller's valuation. A cursed buyer fails to fully account for the fact that the seller's acceptance of their bid depends on the seller's signal. Thus, they tend to bid above equilibrium predictions and may experience regret for winning an asset that is worth less than what they had anticipated. In contrast, a buyer who performs Bayesian inference correctly will account for this information and adjust their estimate accordingly.

Cursedness can occur in common value auctions (Capen et al., 1971; Cassing and Douglas, 1980; Dessauer et al., 1982; Kagel and Levin, 1986; Hendricks et al., 2003), voting (Guarnaschelli et al., 2000; Esponda and Vespa, 2014), cheap talk games (Lim and Zhao, 2024), and signaling games (Lin and Tan, 2025). This paper focuses on one of the simplest environments: the takeover game introduced by Samuelson and Bazerman (1985), which is a two-person ultimatum bargaining game with asymmetric information. The standard takeover game is characterized by one-sided asymmetric information, where the seller, but not the buyer, knows the exact common value of a firm. The firm is worth more to the buyer than the seller. The buyer proposes a bid, which the seller accepts or rejects.

The standard takeover game provides a simple setting in which to study the winner's curse. However, it abstracts from the complexities of real-life transactions. In practice, market participants may have access to private information about the value of an asset. Consider the following scenario: an acquirer makes a bid to take over a firm. The acquirer is privately informed about the value that can be generated by the acquirer's scaling technologies, whereas the owner of the firm is privately informed about the quality of the firm's project. A two-sided information asymmetry exists, because the exact value of the firm is unknown to the acquirer and the owner.

I develop a novel framework based on the takeover game to capture two-sided asymmetric information. Then, I apply Cursed Sequential Equilibrium, introduced by Fong et al. (2024), to predict how the degree of information asymmetry and size of the stakes affect information transmission. The model also predicts the percentage of bids that will be accepted, which serves as a measure of allocative efficiency. These predictions will be tested in the lab from April to October 2025 at University of Virginia. One advantage of experiments is that I can overcome the challenge of pinning down information asymmetries in the field by controlling the degree of information asymmetry between two players to study cursedness. I propose two experiments to test how **information asymmetry** contributes to cursedness in a takeover game. In addition, I will examine whether people can overcome cursedness with **experience in different roles**.

In Experiment 1, I use a within-subjects design and vary the degree of information asymmetry and size of the stakes to study their impact on cursedness. I use three distinct sets of parameters which offer unique equilibrium predictions. Depending on the parameters, the model predicts that there may be full information transmission (separating equilibrium) or no information transmission (pooling equilibrium). I will also study whether the percentage of bids accepted aligns with model predictions to assess allocative efficiency.

In Experiment 2, I propose a between-subjects design to study three channels for gaining experience in different roles. I fix or vary the role (buyer vs. seller) and type (high vs. low) assigned to a subject. The rationale is that experience in different roles and types may provide a chance for a subject to better understand the strategic implications of the choices in their designated role or type. Standard game theory and cursed sequential equilibrium predict that assignment protocols will not affect behavior. However, competing theories, such as the self-confirming equilibrium (Fudenberg and Vespa, 2019), suggest that different assignment protocols could affect behavior. This experiment is an exploratory study to examine whether the predictions of cursed sequential equilibrium hold when different assignment protocols are implemented.

2 Related Literature

There are conflicting views in the literature on whether experience can attenuate cursed behavior. Hendricks et al. (2003) argue that the bidders' tendency to bid more aggressively under more competition is tempered by winner's curse considerations. Dyer et al. (1989) find that both industry experts and less experienced student subjects tend to overbid in sealed-bid, common value auctions. However, Harrison and List (2008) find that experienced bidders are less susceptible to cursedness in familiar environments, even though the same bidders may fall prey to cursedness in unfamiliar environments.

Echoing observations in the field, experimental findings suggest that more aggressive bidding is observed with competition (Kagel and Levin, 1986). Holt and Sherman (1994) find little evidence to support the argument that subjects would overbid in a takeover game for the thrill of winning. Charness and Levin (2009) attribute the winner's curse to a form of bounded rationality, where some people find it difficult to fully account for hypothetical events when they make inferences. Further, Holt and Sherman (2014) find that the winner's curse cannot be explained solely by risk aversion. Martínez-Marquina et al. (2019) use the takeover game to show that individuals find it difficult to perform contingent reasoning in the presence of uncertainty.

Eyster and Rabin (2005) introduce a new equilibrium concept known as the cursed equilibrium to explain the winner's curse. The main idea is that a cursed player does not fully account for the relationship between their opponents' actions and types. Fong et al. (2024) and Cohen and Li (2022) propose the cursed sequential equilibrium and sequential cursed equilibrium, respectively, to extend this solution concept to dynamic games with incomplete information. At a broader level, this work is also related to other behavioral theories, such as Analogy-Based Expectation Equilibrium (ABEE) (Jehiel, 2005; Jehiel and Koessler, 2008), Agent Quantal Response Equilibrium (AQRE) (McKelvey and Palfrey, 1998) and Dynamic Cognitive Hierarchy (DCH) (Lin and Palfrey, 2024), to name a few.

Previous experiments on takeover games focus on cursed behavior under one-sided asymmetric information. This paper contributes to the literature by deriving a class of takeover games to study cursed behavior under two-sided asymmetric information. In addition, this paper applies the cursed sequential equilibrium, a behavioral solution concept that offers precise predictions for how cursedness affects information transmission and allocative efficiency in a takeover game.

3 Theoretical Background

3.1 Setup

I develop a framework based on the takeover game (Samuelson and Bazerman, 1985) to study the behavior of a buyer who makes a bid to buy an asset from a seller under **two-sided information asymmetry**.

Consider a common value setting with two risk-neutral players—the acquirer (buyer) and the owner (seller) of an asset, denoted by $i \in \{b, s\}$. Suppose $\Theta_i = \{\underline{\theta}, \overline{\theta}\}$ is the set of two possible private signals (or types), where $\underline{\theta} < \overline{\theta}$. The set of type profiles is $\Theta \equiv \Theta_b \times \Theta_s$, and p is a commonly known and identical probability distribution over Θ. First, each player independently draws a private signal $\theta_i \in \Theta_i$ with probability $p = Pr(\theta_i = \underline{\theta}) = 1 - Pr(\theta_i = \overline{\theta})$. I specify the common value of an asset v to be a convex combination of private signals

$$v = \beta\theta_b + (1 - \beta)\theta_s \tag{1}$$

where the commonly known $\beta \in [0, 1]$ indicates which player is better informed about v.[1] For $\beta > 0.5$, the buyer is better informed than the seller about v. Conversely, for $\beta < 0.5$, the seller is better informed than the buyer about v.

Next, the buyer makes a take-it-or-leave-it offer $a_b \in A_b = \mathbb{R}_+$ to the seller. After observing the buyer's offer, the seller decides whether to accept ($a_s = Y$) or reject ($a_s = N$) the offer. In other words, the buyer's behavioral strategy is a mapping from their type to action set $\sigma_b : \Theta_b \to A_b$, and the seller's behavioral strategy is $\sigma_s : \Theta_s \times A_b \to A_s$. The set of behavioral strategy profiles is $\Sigma = \Sigma_b \times \Sigma_s$.

The von Neumann-Morgenstern payoff function $\pi_i : \Theta \times A \to \mathbb{R}$ for player i depends on the type and strategy profiles. The payoff functions are:

$$\pi_b(a_b = c, a_s|\theta_b, \theta_s) = \begin{cases} mv - c & if \ a_s = Y \\ 0 & if \ a_s = N \end{cases} \quad and \quad \pi_s(a_s, a_b = c|\theta_b, \theta_s) = \begin{cases} c & if \ a_s = Y \\ v & if \ a_s = N \end{cases}$$

[1] The standard takeover game is characterized by one-sided asymmetric information. This is equivalent to placing a weight of 0 on the buyer's signal and 1 on the seller's signal. In the standard game, the buyer makes a bid to acquire a firm from the seller. Goeree and Offerman (2002) uses a similar expression to capture the precision or quality of a bidder's signal in a common value auction. To the best of my knowledge, this paper is the first to use Equation (1) to study the effect of information asymmetries in a takeover game.

The buyer maximizes their expected payoff $m\mathbb{E}[v|\theta_b] - c$, where m is common knowledge. I assume $m > 1$ to represent potential efficiency gains from an acquisition, which provides an incentive for a deal to occur. This means that an asset is worth more to the buyer than to the seller. One example is when the buyer has access to capital that can scale up the target firm's project. The seller accepts any offer above their valuation $c \geq \mathbb{E}[v|\theta_s, a_b]$. Consistent with the literature on the standard takeover game, I set $m = 1.5$ and $p = 0.5$. Hence, a takeover game is defined by a tuple $\mathcal{T} = \langle \beta, \Theta \rangle$.

3.2 Cursed Sequential Equilibrium

I apply the cursed sequential equilibrium (CSE) concept developed by Fong et al. (2024) to explain the winner's curse in a takeover game with two-sided asymmetric information. CSE extends the cursed equilibrium introduced by Eyster and Rabin (2005) to dynamic games. A cursed player correctly perceives the marginal distribution of their opponent's action, but they misperceive the joint distribution of their opponent's action and type. Put simply, a player forms the wrong belief about how an opponent's action depends on the opponent's type. In a takeover game, a cursed buyer fails to understand that the seller's acceptance of a bid depends on the seller's signal, whereas a cursed seller does not recognize that the buyer's bid depends on the buyer's signal.

Following the literature, I use a single parameter $\chi \in [0, 1]$ to capture the degree of cursedness, or the degree to which a player misperceives the correlation between their opponent's behavioral strategy and type.[2] A fully rational ($\chi = 0$) buyer correctly accounts for how the seller's behavioral strategy depend on the seller's type. When $\chi = 0$, a CSE coincides with a standard sequential equilibrium. A fully cursed ($\chi = 1$) buyer believes that the seller's behavioral strategy is independent of the seller's type. A χ-cursed buyer believes that the seller adopts the average behavioral strategy with probability χ, regardless of the seller's private signal, and the seller adopts the true (Bayesian) behavioral strategy with probability $1 - \chi$. Since it is well-documented empirically that people tend to exhibit fully cursed behavior (Charness and Levin, 2009; Esponda and Vespa, 2014; Lin, 2023; Lin and Palfrey, 2024), I will focus on the case where $\chi = 1$.

In equilibrium, a sequentially rational seller will accept any bid above the expected value $\mathbb{E}[v|\theta_s, a_b]$. In the case where the buyer and seller are fully cursed ($\chi = 1$), the seller incorrectly believes that the buyer's bid does not depend on the buyer's type. Hence, the seller's posterior on the buyer's type after observing a bid is the same as the seller's prior, which is the simple average of possible signals $\frac{\underline{\theta}+\overline{\theta}}{2}$.

The seller's acceptance threshold is a weighted sum of their expectation of the buyer's signal and their own signal. Since the seller's acceptance threshold depends on their type, there are two bids of interest: $\underline{C} \equiv \beta\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right) + (1-\beta)\underline{\theta}$ and $\overline{C} \equiv \beta\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right) + (1-\beta)\overline{\theta}$. Given the seller's behavioral strategy, offering any $c \notin \{\underline{C}, \overline{C}\}$ cannot be supported by a CSE, because the buyer is better off adjusting their bid to either $\underline{C}$ or $\overline{C}$ to maximize

[2] It is reasonable to assume that a player thinks that the other player thinks like how they think, when the exact value of the asset is unknown to both of them and they both receive private signals about this value. Hence, I assume that the buyer and seller are equally susceptible to the winner's curse $\chi \equiv \chi_b = \chi_s$. This captures a scenario in which the buyer's belief about the relationship between the seller's behavioral strategy and type is the same as the seller's belief about the relationship between the buyer's behavioral strategy and type.

their expected payoff. A bid $\underline{C}$ is accepted with probability $\frac{1}{2}$, because it is only accepted by a low type seller, whereas a bid $\overline{C}$ is always accepted by both types.

From the buyer's perspective, the seller's average strategy in a CSE is as follows. The seller will always reject any bid below a low type seller's acceptance threshold. Any bid between the acceptance thresholds of a low type seller and high type seller will only be accepted by a low type seller, so, on average, a bid in this interval is accepted with probability $\frac{1}{2}$. Any bid above a high type seller's acceptance threshold will always be accepted by both types of sellers.

A fully cursed buyer incorrectly believes that the seller's behavioral strategy is independent of the seller's signal, so the buyer's expectation of the seller's type is the simple average of possible signals $\frac{\underline{\theta}+\overline{\theta}}{2}$. The buyer's expected value of the asset is a weighted sum of their own signal and their expectation of the seller's signal $\mathbb{E}[v|\theta_b] = \beta\theta_b + (1-\beta)\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right)$. The buyer's expected payoff is

$$\mathbb{E}\pi_b(a_b, \overline{\sigma}_s|\theta_b) = \overline{\sigma}_s(Y|\theta_b, a_b)\left\{1.5\left(\beta\theta_b + (1-\beta)\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right)\right) - c\right\}$$

which is the probability of acceptance, derived from the seller's average behavioral strategy $\overline{\sigma}_s$, times the buyer's valuation less the bid.

Proposition 1 *The unique CSE of a takeover game $\mathcal{T} = \langle\beta, \Theta\rangle$ is characterized by the following conditions:*

1. *a low type seller will accept a bid iff $c \geq \beta\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right) + (1-\beta)\underline{\theta} \equiv \underline{C}$,*
   a high type seller will accept a bid iff $c \geq \beta\left(\frac{\underline{\theta}+\overline{\theta}}{2}\right) + (1-\beta)\overline{\theta} \equiv \overline{C}$,
2. *when $K < \underline{\theta}$, both types of buyers offering $c = \underline{C}$ is a pooling equilibrium,*
3. *when $K > \overline{\theta}$, both types of buyers offering $c = \overline{C}$ is a pooling equilibrium, and*
4. *when $\underline{\theta} \leq K \leq \overline{\theta}$, there is a separating equilibrium where a high type buyer offers $c = \overline{C}$ and a low type buyer offers $c = \underline{C}$*

where

$$K \equiv \left(\frac{5}{6\beta} - \frac{1}{2}\right)\overline{\theta} + \left(-\frac{7}{6\beta} + \frac{3}{2}\right)\underline{\theta}.$$

The intuition behind Proposition 1 is as follows. When the low signal $\underline{\theta}$ is sufficiently high, buyers will pool at a low bid $\underline{C}$. When the high signal $\overline{\theta}$ is sufficiently low, buyers will pool at a high bid $\overline{C}$. Otherwise, a high type buyer will offer a high bid $\overline{C}$ and a low type buyer will offer a low bid $\underline{C}$. Henceforth, I shall refer to the pooling equilibrium at the low bid as P-Low, pooling equilibrium at the high bid as P-High, and separating equilibrium as S.

Corollary 1 *P-Low and P-High are pooling CSE for any $\chi \in [0, 1]$.*

This result follows from Proposition 5 in Fong et al. (2024). In a pooling equilibrium, all types of players choose the same action. A player cannot make any inference about another player's type. Put differently, a player's posterior is the same as their prior, and their posterior is independent of χ. By Corollary 1, any pooling CSE is a sequential equilibrium. This means that P-Low and P-High are pooling CSE when the buyer and seller are fully rational ($\chi = 0$). In other words, CSE offers a unique refinement of these two pooling equilibria. CSE is a type of belief-based refinement, which is different from other belief-based refinements that are commonly used in signaling games, such as the "Intuitive Criterion" (Cho and Kreps, 1987) and the "Divinity Criterion" (Banks and Sobel, 1987).

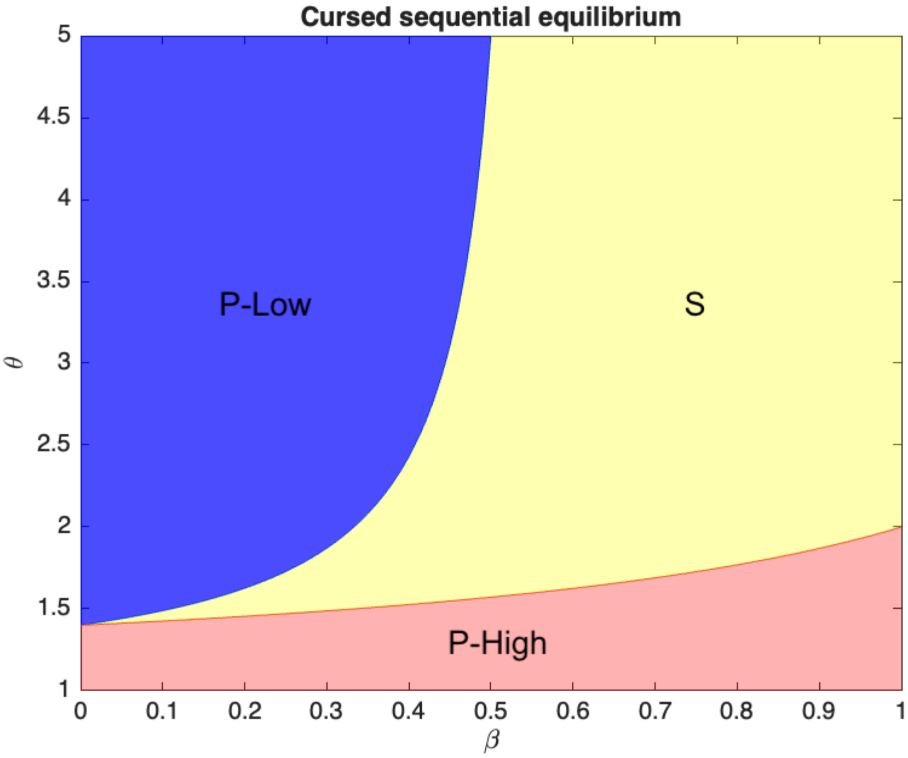

Figure 1: The set of CSE when $m = 1.5$, $p = 0.5$, and $\theta = \overline{\theta}/\underline{\theta}$.

Figure 1 illustrates the set of CSE on a (β,θ)-plane. Depending on the information weight β and size of the stakes θ, a high type player may behave differently from a low type player, or they may exhibit the same behavior in equilibrium. For a given (β,θ) pair, the model offers a unique equilibrium prediction. This allows me to test the theory and perform causal inference using experimental data.

In terms of welfare, the efficient allocation is that the buyer acquires the asset, because the asset is worth more to the buyer than the seller. The model predicts that in P-Low, a sale happens with probability $\frac{1}{2}$, because only a low type seller accepts a low bid. In S, a sale happens with probability $\frac{3}{4}$, because a low type seller accepts both high and low bids, and a high type seller only accepts a high bid. In P-High, a sale always happens, because both types of sellers accept a high bid. I will test these predictions in the experiments to examine efficiency in a takeover game under asymmetric information.

4 Experimental Design

The takeover game provides a tractable setting to study how a player's misperception of another player's information set affect behavior under two-sided asymmetric information.

Identifying information asymmetry with field data can be challenging. In contrast, a lab experiment is ideal for creating an environment where I can precisely control the degree of information asymmetry between two players to test model predictions. Specifically, I propose two experiments to study how information asymmetry affects cursed behavior in a takeover game, and whether people can overcome cursedness with experience in different roles.

Experiment 1: Information Asymmetry

I use a within-subjects design with three treatments to study how two-sided asymmetric information contributes to the misperception of information sets in a takeover game. Each subject will participate in all three treatments, so I can observe how the same person responds to different degrees of information asymmetry.

There is extensive evidence from experimental and field settings that people exhibit cursed behavior, so I will focus on the case in which a cursed buyer makes a bid to acquire an asset from a cursed seller. Following the literature, I will set $m = 1.5$ so that the experimental results are comparable. The model predicts that high type and low type buyers may pool or separate in equilibrium, depending on the degree of information asymmetry β and the ratio of signals $\theta \equiv \overline{\theta}/\underline{\theta}$. The ratio of signals θ serves as a proxy for the size of the stakes.

To test the theory, I select three sets of parameters $(\beta, \theta) = (0.8, 1.2)$, $(\beta, \theta) = (0.8, 4)$, and $(\beta, \theta) = (0.2, 4)$ as treatments. The parameters $(\beta, \theta) = (0.8, 1.2)$ will be used in the **P-High** treatment, where all buyers are predicted to offer a high bid, regardless of their type (pooling CSE at high bid). The parameters $(\beta, \theta) = (0.2, 4)$ will be used in the **P-Low** treatment, and all buyers are predicted to offer a low bid, regardless of their type (pooling CSE at low bid). The parameters $(\beta, \theta) = (0.8, 4)$ will be used in the **S** treatment; the model predicts that a high type buyer will choose a high bid and a low type buyer will choose a low bid (separating CSE). Figure 2 illustrates the three parameter sets and the corresponding CSE predictions. I will also compare the percentage of accepted bids with the predicted percentage of accepted bids in each treatment to assess whether the market is as efficient as theory predicts.

There will be a total of 15 rounds in each session. The three treatments will be repeated five times each. This repetition allows me to examine how a subject's behavior changes over time. To counterbalance order effects, I randomize the order in which the parameter sets appear in each session.

I will recruit a total of 112 subjects, with 8 subjects—4 buyers and 4 sellers—in each session. At the start of a session, each subject is randomly assigned to be a buyer or seller, and a subject will remain as a buyer or seller throughout a session. I adopt neutral labels—"buyer" and "seller" instead of "raider" and "target firm"—to prevent confounding framing effects.

At the start of each round, subjects will be split into groups of two using the **random matching protocol** without feedback to mitigate reputation building effects. To obtain a balanced assignment of types, 2 buyers and 2 sellers will be randomly assigned as high type players; 2 buyers and 2 sellers will be randomly assigned as low type players. With this assignment, I will obtain 140 observations from high type buyers and 140

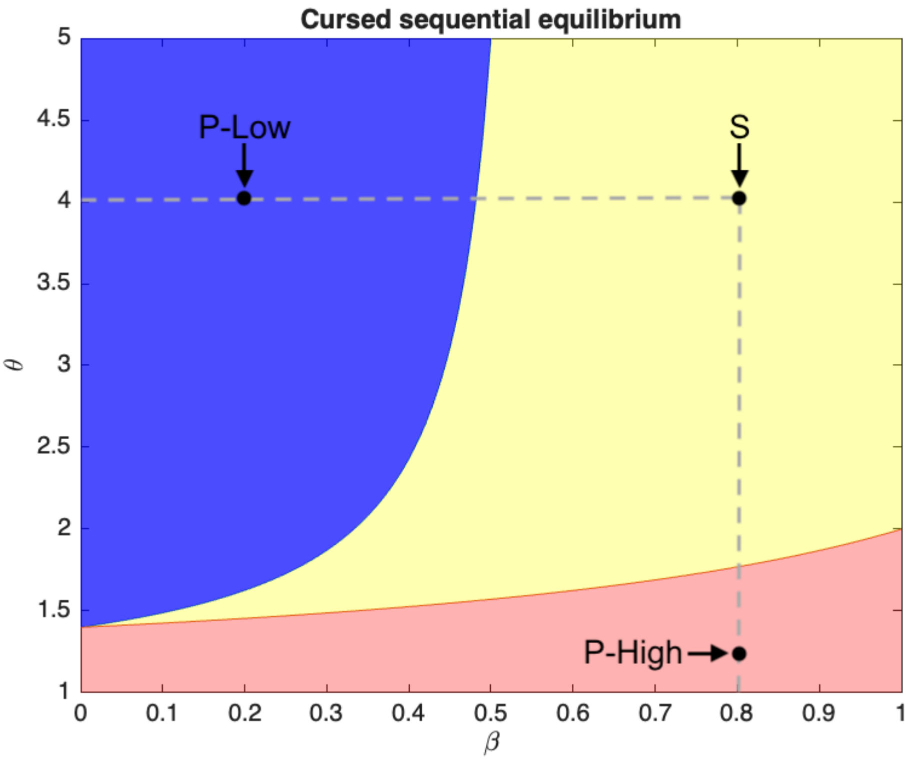

Figure 2: CSE for a fully cursed buyer and seller when $m = 1.5$, $p = 0.5$, and $\theta = \overline{\theta}/\underline{\theta}$.

observations from low type buyers for each treatment, which will provide enough statistical power for econometric analysis.

Figures 3 and 4 illustrate the user interface for the buyer and seller, respectively. The experiment is programmed in oTree (Chen et al., 2016), an online platform to implement web-based interactive experiments.

Experiment 2: Experience in different roles

I use a between-subjects design to examine whether experience can mitigate the winner's curse in a takeover game. In this experiment, I introduce three channels for gaining experience in a takeover game. The rationale is that experience in different roles and types may provide a chance for a subject to better understand the strategic implications of the choices in their designated role or type. From the perspective of standard game theory and CSE, the assignment protocols should not affect behavior. Yet, some theories, such as self-confirming equilibrium (Fudenberg and Vespa, 2019), suggest that different assignment protocols could affect behavior. This experiment is an exploratory study to examine whether the predictions of cursed sequential equilibrium hold when different assignment protocols are implemented. The findings will broadly impact the field of experimental economics by addressing a long-standing question in experimental methodology: whether role assignment protocols can affect behavior in a lab.

The three treatments are: **Fixed Role** × **Fixed Type**, **Random Role** × **Fixed Type**, and **Random Role** × **Random Type**. Each participant will only participate in one of three treatments to prevent spillover effects across treatments.

In the Fixed Role treatment, a subject will remain in the same role that they have

Round 1

You are the **buyer**.

You have an endowment of **$6.00** to buy the asset.

The asset is worth **$V** to the seller, where **$V** is **0.2** times **your private signal** of **$1.00** plus **0.8** times **the seller's private signal**, which is equally likely to be **$1.00** or **$4.00**.

Hence, **$V** = **$0.20** + **?**, where **?** is equally likely to be **$0.80** or **$3.20**.

This means that there is a **50%** chance that **$V** is **$1.00** and a **50%** chance that **$V** is **$3.40**.

The asset is worth **1.5** times **$V** to you, so there is a **50%** chance that the asset is worth **$1.50** and a **50%** chance that the asset is worth **$5.10** to you.

To summarize, based on **your private signal** of **$1.00**:

Chance	Value to the seller, $V	Value to you, 1.5 x $V
50%	$1.00	$1.50
50%	$3.40	$5.10

Remember that the seller only knows that **your private signal** is equally likely to be **$1.00** or **$4.00**.

- If the seller **accepts** your bid, your earnings for this round will be **1.5 x $V** minus **your bid**.
- If the seller **rejects** your bid, your earnings for this round will be **$0**.

What is your bid to the seller?

$

Figure 3: The buyer's decision screen.

Round 1

You are the **seller**. You own the asset.

The asset is worth **$V** to you, where **$V** is **0.8** times **your private signal** plus **0.2** times **the buyer's private signal**.

Your private signal is **$1.00**.

The buyer's private signal is equally likely to be **$1.00** or **$4.00**.

Hence, **$V** = **$0.80** + **?**, where **?** is equally likely to be **$0.20** or **$0.80**.

This means that there is a **50%** chance that **$V** is **$1.00** and a **50%** chance that **$V** is **$1.60**.

The asset is worth **1.5** times **$V** to the buyer, so there is a **50%** chance that the asset is worth **$1.50** and a **50%** chance that the asset is worth **$2.40** to the buyer.

To summarize, based on **your private signal** of **$1.00**:

Chance	Value to you, $V	Value to the buyer, 1.5 x $V
50%	$1.00	$1.50
50%	$1.60	$2.40

Remember that the buyer only knows that **your private signal** is equally likely to be **$1.00** or **$4.00**.

The buyer's bid is $3.00.

- If you **accept** the bid, your earnings for this round will be $3.00.
- If you **reject** the bid, your earnings for this round will be **$V**.

Do you accept or reject the bid $3.00?

Accept ◯ **Reject** ◯

Figure 4: The seller's decision screen.

been assigned to, so a subject will stay as a buyer or seller throughout a session. In the Random Role treatment, each subject is randomly assigned to be either a buyer or seller at the start of every round. A subject will make a bid as a buyer in one round and accept or reject a bid as a seller in a different round.

In the Fixed Type treatment, each subject's type (high or low) stays the same throughout a session. In the Random Type treatment, every subject randomly draws a type at the start of each round. A subject will make decisions as a high type player in one round and as a low type player in a different round. To achieve a balanced assignment, 2 buyers and 2 sellers will be randomly assigned as high type players; 2 buyers and 2 sellers will be randomly assigned as low type players.

Subjects in Experiment 1 will be assigned fixed roles, and they will draw different types in each round. Hence, the data from Experiment 1 will be used as a benchmark to explore how experience in different roles and types impact long-run behavior in a takeover game.

Implementation

I plan to run both Experiment 1 and 2 at Vecon Lab (Experimental Economics Laboratory) at the University of Virginia from April to October 2025. Both experiments are programmed in oTree (Chen et al., 2016), a platform to implement online experiments. University of Virginia students will be recruited as subjects.

5 Hypotheses and Analysis Plan

Hypotheses Testing for Experiment 1

In Experiment 1, the theory predicts that, depending on the degree of information asymmetry β and size of the stakes θ, a pooling or separating CSE may be observed. The model predicts that there are two pooling CSE and one separating CSE. To test the model, I precisely vary the degree of information asymmetry and size of the stakes. I will use c_H and c_L to denote the observed bids of high and low type buyers, respectively.

Hypothesis 1 *In the P-High treatment, both high and low type buyers offer the same bid amount, and their bids equal the predicted bid* $c_H = c_L = \overline{C}$.

Hypothesis 2 *In the P-Low treatment, both high and low type buyers offer the same bid amount, and their bids equal the predicted bid* $c_H = c_L = \underline{C}$.

Hypothesis 3 *In the S treatment, high type buyers offer the predicted high bid, and low type buyers offer the predicted low bid* $c_H = \overline{C}$, $c_L = \underline{C}$.

As a measure of welfare, I will compare the percentage of accepted bids w in each treatment with the predicted percentage of accepted bids.

Hypothesis 4 *In the P-Low treatment,* $w_{P-Low} = 50\%$. *In the S treatment,* $w_S = 75\%$. *In the P-High treatment,* $w_{P-High} = 100\%$.

Hypotheses Testing for Experiment 2

In Experiment 2, I adopt different role and type assignment protocols. I will use the three sets of parameters (β, θ) from Experiment 1, so that the results are comparable. For a given (β, θ) pair, both Nash equilibrium and CSE predict that subjects will behave the same in all treatments, regardless of whether they stay in a fixed role, or they switch roles in a session. Similarly, a high type subject who remains a high type throughout a session should behave the same as a high type subject who has played as different types in different rounds. Figure 5 summarizes the four hypotheses that will be tested using data from Experiments 1 and 2.

Hypothesis 5 *The behavior in the Fixed Role × Random Type treatment in Experiment 1 will not differ from the behavior in the Random Role × Random Type treatment in Experiment 2.*

Hypothesis 6 *The behavior in the Random Role × Random Type treatment in Experiment 1 will not differ from the behavior in the Random Role × Fixed Type treatment in Experiment 2.*

Hypothesis 7 *The behavior in the Random Role × Fixed Type treatment will not differ from the behavior in the Fixed Role × Fixed Type treatment in Experiment 2.*

Hypothesis 8 *The behavior in the Fixed Role × Fixed Type treatment will not differ from the behavior in the Fixed Role × Random Type treatment in Experiment 2.*

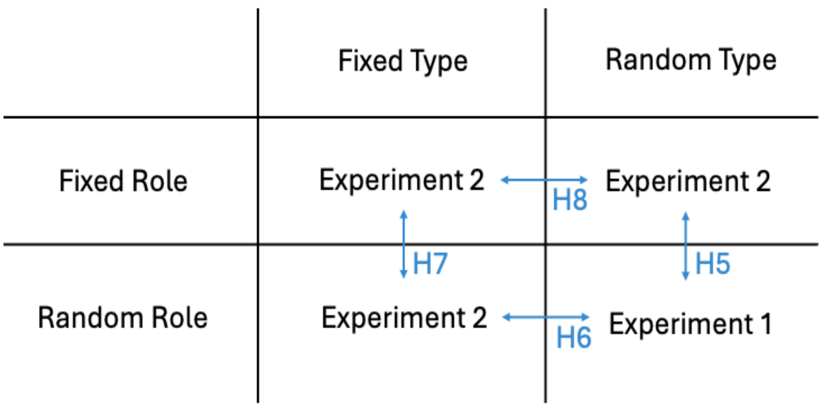

Figure 5: Hypotheses 5-8 that will be tested with data from Experiments 1 and 2.

Structural Estimation

Aside from testing the treatment effects non-parametrically, I will use a structural estimation approach proposed by Lin (2023) to pin down the choice probabilities using the Quantal Cursed Sequential Equilibrium (QCSE) model and examine its goodness-of-fit. QCSE combines Agent Quantal Response Equilibrium (AQRE) by McKelvey and Palfrey (1998) and CSE. One advantage of structural estimation is that I can compare how well QCSE explains the data compared to alternative models, such as AQRE and the Dynamic Cognitive Hierarchy model (Lin and Palfrey, 2024).

In the experiments, I will discretize the action space of the buyer to facilitate structural estimation. For example, if $\underline{\theta} = 1$ and $\overline{\theta} = 4$, the buyer will be able to choose a bid in the interval $[0, 4]$ and adjust their bid in 0.01 increments. This yields 401 possible actions. The buyer believes that the average behavioral strategy profile of the seller is:

$$\overline{\sigma}_s(a_s = Y|\theta_b, a_b) = \sum_{\theta_s \in \Theta_s} \mu^\chi(\theta_s|\theta_b, a_b)\sigma_s^\chi(a_s = Y|\theta_s, a_b).$$

where μ^χ and σ^χ are the belief system and strategy profile of a χ-cursed player, respectively. The seller believes that the average behavioral strategy profile of the buyer is:

$$\overline{\sigma}_b(a_b|\theta_s) = \sum_{\theta_b \in \Theta_b} \mu^\chi(\theta_b|\theta_s)\sigma_b^\chi(a_b|\theta_b).$$

A cursed player form incorrect beliefs about the relationship between their opponent's strategy and type. A χ-cursed buyer believes the seller uses a χ-weighted sum of average (type-independent) behavioral strategy and true (Bayesian) behavioral strategy:

$$\sigma_s^\chi(a_s = Y|\theta_s, \theta_b, a_b) = \chi\overline{\sigma}_s(a_s = Y|\theta_b, a_b) + (1-\chi)\sigma_s(a_s = Y|\theta_s, a_b).$$

This updating rule is called the χ-cursed Bayes' rule. Denote the continuation value of a χ-cursed player i as $\overline{\pi}_i(a, \sigma|\mathcal{I}_i)$, where $\mathcal{I}_i$ is player i's information set.

Following the quantal response literature, I use $\lambda \in [0, \infty)$ to capture the precision of choices. I assume the choice probabilities follow a multinomial logit distribution. An assessment (μ,σ) is a QCSE if the belief system of a player is derived from the χ-cursed Bayes' rule, and at each information set $\mathcal{I}_i$, the probability of player i choosing $a \in A_i$ is

$$\sigma_i(a|\mathcal{I}_i) = \frac{e^{\lambda\overline{\pi}_i(a,\sigma|\mathcal{I}_i)}}{\sum_{a' \in A_i} e^{\lambda\overline{\pi}_i(a',\sigma|\mathcal{I}_i)}}$$

For each information set $\mathcal{I}_i$, fixing λ and χ, QCSE uniquely predicts the choice probability of each a_i. This is denoted as $\overline{Q}(a_i|\mathcal{I}_i)$. The log-likelihood function can be derived by aggregating over each player i, action a_i, and information set $\mathcal{I}_i$:

$$ln\, L^{\overline{Q}}(\lambda, \chi) = \sum_i \sum_{\mathcal{I}_i \in \Pi_i} \sum_{a_i \in A_i(\mathcal{I}_i)} \mathbb{1}\{a_i, \mathcal{I}_i\}\, ln\, [\overline{Q}(a_i|\mathcal{I}_i), \lambda, \chi)],$$

where $\mathbb{1}\{a_i, \mathcal{I}_i\} = 1$ for a player i who chooses action a_i at information set $\mathcal{I}_i$.

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A Supplemental Appendix (For Online Publication)

Data from Experiment 1

Table A.1: OLS Regression Results

	Buyer's Bid	Seller's Acceptance %
Own Signal	0.508***	-0.064***
	(0.023)	(0.011)
Own Signal × InfoWeight	0.204***	-0.112***
	(0.031)	(0.005)
Risk Aversion	-0.338***	0.084*
	(0.060)	(0.048)
Constant	1.075***	0.735***
	(0.076)	(0.035)
R-squared	0.575	0.157

N=210. Standard errors are clustered at the session level.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.