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TESTING THE QUANTAL RESPONSE HYPOTHESIS

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Abstract

This paper develops a formal test for consistency of players' behavior in a series of games with the quantal response equilibrium (QRE). The test exploits a characterization of the equilibrium choice probabilities in a QRE as the gradient of a convex function, which thus satisfies the *cyclic monotonicity* inequalities. Our testing procedure utilizes recent econometric results for moment inequality models. We assess the performance of the test using both Monte Carlo simulation and lab experimental data from a series of generalized matching pennies games. Our experimental findings are consistent with the literature: the joint hypothesis of QRE, risk neutrality and player role homogeneity is rejected in the pooled data, but cannot be rejected in the individual data for over half of the subjects. By considering subsets of cycle monotonicity inequalities, our approach also highlights the nature of QRE consistency violations.

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1 Introduction

Many important economic situations arise as an interaction of individual agents who each independently maximize their utility given their beliefs about the others' action plans. Such situations are formally modelled using game theory, where Nash equilibrium has become the de facto "gold standard". However, numerous laboratory experiments demonstrated that people systematically deviate from the Nash equilibrium predictions in some games while follow them in others (e.g., Goeree & Holt (2001)).

One way to account for these deviations is to introduce random shocks to the players' payoff functions as it is done in discrete choice models (e.g., McFadden (1974)). But in a game with several players, these shocks will affect payoffs, and hence players' actions, in an endogeneous manner. The precise way of formulating the idea of equilibrium in such a context was proposed by McKelvey & Palfrey (1995), who introduced the Quantal Response Equilibrium (QRE): a solution concept that relaxes Nash in a very natural fashion while preserving the idea of equilibrium. Essentially, the main property of a QRE is that for each player strategies with higher expected (equilibrium) payoffs must be played with a higher probability than strategies with lower expected payoffs.

QRE – in particular its logit formulation, which involves a single estimable parameter – has become a popular tool in experimental economics because typically it provides an

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improved fit to the experimental data. It turned out, though, that without imposing strong assumptions on the shock distributions, QRE can rationalize any outcome in a given game (see Haile, Hortacsu, & Kosenok (2008), hereafter HHK). The good news, though, is that QRE consistency can be tested in a semi-parametric manner (without assuming specific parametric assumptions on the distribution of utility shocks), and HHK describe several approaches for testing (without discussing the econometric implementation of such tests).

Building on this earlier work, in this paper we introduce a new approach for testing QRE consistency. Our approach is based on the property of *cyclic monotonicity*, a notion from convex analysis. Data satisfying this property can be generated by *some* QRE of the underlying game. One important advantage of our approach, as in HHK, is that it is semi-parametric (no need to assume extreme value shocks). Moreover, the cyclic monotonicity conditions take the form of joint inequality restrictions on the underlying choice frequencies and payoffs from the underlying game; hence, we are able to apply tools and methodologies from the recent econometric literature on moment inequality models to this setting.

In order to illustrate how our test works, we use the data from a lab experiment on generalized matching pennies where the same subjects play a sequence of several games. We find that QRE is rejected soundly when data is pooled across all subjects and all plays of each game. But when we consider subjects individually, we find that the QRE hypothesis cannot be rejected for upwards of half the subjects. This suggests that there is substantial heterogeneity in behavior across subjects. Moreover, the congruence of subjects' play with QRE varies substantially depending on whether subjects are playing in the role of the row vs. column player.

Our use of the notion of cyclic monotonicity to test the QRE hypothesis appears new to the experimental game theory literature. Elsewhere, cyclic monotonicity has been studied in the context of multidimensional mechanism design. In particular, the papers by Rochet (1987), Saks & Yu (2005), Lavi & Swamy (2009), Ashlagi et al. (2010), and Archer & Kleinberg (2014) (summarized in Vohra (2011, Chapter 4)), relate the incentive compatibility (truthful implementation) of a mechanism to its cyclic monotonicity properties.

The rest of the paper is organized as follows. Section 2 presents the QRE approach. Section 3 introduces the test for the QRE hypothesis, and Section 4 discusses the moment inequalities for testing. Section 5 discusses the statistical properties of the test. Section

6 describes our experiment, with subsections 6.1 and 6.2 presenting the experimental design and results respectively. Finally, Section 7 concludes.

2 QRE background

In this section we briefly review the main ideas behind the QRE approach. We use the notation from McKelvey & Palfrey (1995).

Consider a finite n-person game $G(N, \{S_i\}_{i\in N}, \{u_i\}_{i\in N})$. The set of strategies available to player i is indexed by $j = 1, \ldots, J_i$, so that $S_i = \{s_1, \ldots, s_{J_i}\}$. We will occasionally abuse notation and write $j \in S_i$. Let $\boldsymbol{s}$ denote an n-vector strategy profile; let s_i and $\boldsymbol{s}_{-i}$ denote player i's (scalar) action and the vector of actions for all players other than i. In terms of notation, all vectors are denoted by bold letters. Let p_{ij} be the probability that player i chooses action j, and $\boldsymbol{p}_i$ denote the vector of player i's choice probabilities. Let $\boldsymbol{p} = (\boldsymbol{p}_1, \ldots, \boldsymbol{p}_n)$ denote the vector of probabilities across all the players. Player i's utility function is given by $u_i(s_i, \boldsymbol{s}_{-i})$. At the time she chooses her action, she does not know what actions the other players will play. Define the expected utility that player i gets from playing a pure strategy s_{ij} when everyone else's joint strategy is $\boldsymbol{p}_{-i}$ as

$$u_{ij}(\boldsymbol{p}) \equiv u_{ij}(\boldsymbol{p}_{-i}) = \sum_{\boldsymbol{s}_{-i}} p(\boldsymbol{s}_{-i}) u_i(s_{ij}, \boldsymbol{s}_{-i}),$$

where $\boldsymbol{s}_{-i} = (s_{kj_k})_{k\in N_{-i}}$, and $p(\boldsymbol{s}_{-i}) = \prod_{k\in N_{-i}} p_{kj_k}$.

In the QRE framework uncertainty is generated by players' making "*mistakes*". This is modelled by assuming that, given her beliefs about the opponents' actions $\boldsymbol{p}_{-i}$, when choosing her action, player i does not choose the action j that maximizes her expected utility $u_{ij}(\boldsymbol{p})$, but rather chooses the action that maximizes $u_{ij}(\boldsymbol{p}) + \varepsilon_{ij}$, where ε_{ij} represents a preference shock at action j. For each player $i \in N$ let $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \ldots, \varepsilon_{iJ_i})$ be drawn according to an absolutely continuous distribution F_i with mean zero. Then an expected utility maximizer, player i, given beliefs $\boldsymbol{p}$, chooses action j iff

$$u_{ij}(\boldsymbol{p}) + \varepsilon_{ij} \geq u_{ij'}(\boldsymbol{p}) + \varepsilon_{ij'}, \quad \forall j' \neq j.$$

Since preference shocks are random, the probability of choosing action j given beliefs $\boldsymbol{p}$, denoted $\pi_{ij}(\boldsymbol{p})$, can be formally expressed as

$$\begin{aligned}\pi_{ij}(\boldsymbol{p}) &\equiv \mathbb{P}\left(j = \arg \max_{j' \in \{1,\ldots,J_i\}} \{u_{ij'}(\boldsymbol{p}) + \varepsilon_{ij'}\}\right) \\ &= \int_{\left\{\boldsymbol{\varepsilon}_i \in \mathbb{R}^{J_i} \mid \ u_{ij}(\boldsymbol{p})+\varepsilon_{ij} \geq u_{ij'}(\boldsymbol{p})+\varepsilon_{ij'} \ \ \forall j' \in \{1,\ldots,J_i\}\right\}} dF_i(\boldsymbol{\varepsilon}_i) \end{aligned} \tag{1}$$

Then a quantal response equilibrium is defined as a set of choice probabilities $\left\{\pi^*_{ij}\right\}$ such that for all $(i,j) \in N \times \{1,\ldots,J_i\}$,

$$\pi^*_{ij} = \pi_{ij}(\boldsymbol{\pi}^*)$$

Throughout, we assume that all players' preference shock distributions are *invariant*; that is, the distribution does not depend on the payoffs:

Assumption 1. *(Invariant shock distribution) For all realizations $\boldsymbol{\varepsilon}_i := (\varepsilon_{i1},\ldots,\varepsilon_{iJ_i})$ and all payoff functions $u_i(\cdot)$, we have $F_i(\boldsymbol{\varepsilon}_i | u_i(\cdot)) = F_i(\boldsymbol{\varepsilon}_i)$.*

Such an invariance assumption was also considered in HHK's study of the quantal response model, and also assumed in most empirical implementations of QRE.[1]

QRE as a noisy Nash equilibrium. As noted before, QRE captures the idea that players make mistakes when they choose optimal strategies. According to this, the concept of QRE may be seen as a "*noisy*" version of a Nash equilibrium (NE). This way of understanding QRE has been recognized by the literature on learning on games. As a matter of fact, this literature has coined the term of *smooth best responses* (Fudenberg & Levine, 1998) and *perturbed best responses* (Hofbauer & Sandholm, 2002) to refer to QRE.

A key insight from this literature is the explicit formulation of a QRE as a noisy version of a Nash equilibrium. In particular, Hofbauer & Sandholm (2002) show that a QRE can be seen as the Nash equilibrium of a perturbed game in which each player chooses the mixed strategy that maximizes the difference between her expected payoffs and a *penalty-entropy* term. To see the intuition behind this result, consider the special case of logit QRE. In this case, their result is equivalent to saying that $\boldsymbol{\pi}^*$ is a QRE if

[1] Most applications of QRE assume that the utility shocks follow a logistic distribution, regardless of the magnitude of payoffs. One exception is McKelvey, Palfrey, & Weber (2000), who allow the logit-QRE parameter to vary across different games. This direction is further developed in Rogers, Palfrey, & Camerer (2009).

and only if for each player $i \in N$, π_i^* maximizes

$$\underbrace{\sum_{j=1}^{J_i} u_{ij}(\boldsymbol{\pi}_{-i}^*)\pi_{ij}}_{\text{Expected payoff}} - \underbrace{\lambda \sum_{j=1}^{J_i} \pi_{ij} \ln(\pi_{ij})}_{\text{Perturbation}}$$

where $\lambda > 0$ is the localization parameter of the logistic distribution. It is straightforward to see that solving for π_i^* we obtain the logit choice probabilities.

From the previous specification it follows that the logit QRE is just a noisy NE, where the noise in players' payoffs is captured by the perturbation (entropy) $-\lambda \sum_{j=1}^{J_i} \pi_{ij} \ln(\pi_{ij})$. It is easy to see that when $\lambda = 0$, a QRE coincides with a Nash equilibrium; for $\lambda > 0$, a QRE will diverge from NE.[2]

3 A test based on convex analysis

In this section we propose a test for the QRE hypothesis. We start by defining the following function:

$$\varphi^i(\boldsymbol{u}_i(\boldsymbol{\pi})) \equiv \mathbb{E}\left[\max_{j \in S_i}\{u_{ij}(\boldsymbol{\pi}) + \varepsilon_{ij}\}\right]$$

In the discrete choice model literature, the expression $\varphi(\boldsymbol{u})$ is known as the social surplus function.[3] Importantly, this function is smooth and convex. Now the QRE probabilities $\pi_{ij}(\boldsymbol{\pi}^*)$ can be expressed as

$$\boldsymbol{\pi}_i^* = \boldsymbol{\nabla}\varphi^i(\boldsymbol{u}_i(\boldsymbol{\pi}^*)) \tag{2}$$

This follows from the well-known Williams-Daly-Zachary theorem from discrete-choice theory (which can be considered a version of Roy's Identity for discrete choice models;

[2]Beyond the logit case, an analogous perturbation representation exists for the case where for each player $i \in N$ the random variables $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \ldots, \varepsilon_{iJ_i})$ are drawn according to an absolutely continuous distribution F_i with mean zero. For this general case, Hofbauer & Sandholm (2002) show that the perturbation term is given by a strictly convex function $V_i(\pi_i)$, and $\boldsymbol{\pi}^*$ is a QRE if and only if for each player $i \in N$, π_i^* maximizes $\sum_{j=1}^{J_i} u_{ij}(\boldsymbol{\pi}_{-i}^*)\pi_{ij} - V_i(\pi_i)$. For details, see Cominetti, Melo, & Sorin (2010) and Mertikopoulos & Sandholm (2014).

[3]For details see McFadden (1981).

see Rust (1994, p.3104)). Namely, assuming sufficient smoothness of F_i, one can write

$$\begin{aligned}
\frac{\partial \varphi^i(\boldsymbol{u}_i(\boldsymbol{\pi}^*))}{\partial u_{ij}(\boldsymbol{\pi}^*)} &= \frac{\partial}{\partial u_{ij}(\boldsymbol{\pi}^*)} \int_{\mathbb{R}^{J_i}} \left[\max_{\ell \in S_i} \{ u_{i\ell}(\boldsymbol{\pi}^*) + \varepsilon_{i\ell} \} \right] dF_i(\boldsymbol{\varepsilon}_i) \\
&= \int_{\mathbb{R}^{J_i}} \frac{\partial}{\partial u_{ij}(\boldsymbol{\pi}^*)} \left[\max_{\ell \in S_i} \{ u_{i\ell}(\boldsymbol{\pi}^*) + \varepsilon_{i\ell} \} \right] dF_i(\boldsymbol{\varepsilon}_i) \\
&= \int_{\left\{ \boldsymbol{\varepsilon}_i \in \mathbb{R}^{J_i} \mid \; u_{ij}(\boldsymbol{\pi}^*) + \varepsilon_{ij} \geq u_{i\ell}(\boldsymbol{\pi}^*) + \varepsilon_{i\ell} \;\; \forall \ell \in S_i \right\}} dF_i(\boldsymbol{\varepsilon}_i) \\
&= \pi_{ij}(\boldsymbol{\pi}^*)
\end{aligned}$$

Thus if Eq. (2) holds for all players i, then $\left\{ \pi^*_{ij} \right\}$ is a quantal response equilibrium.

Eq. (2) characterizes the QRE choice probabilities as the gradient of the convex function φ. It is well-known (see Rockafellar (1970, Theorem 24.8)) that the gradient of a convex function satisfies a *cyclic monotonicity* property. This property is the generalization, for functions of several variables, of the fact that the derivative of a univariate convex function is monotone nondecreasing.

To define cyclic monotonicity in our setting, consider a sequence of games characterized by the same set of choices for each player, but distinguished by payoff differences. Let $[\boldsymbol{\pi}_i^*]^m$ denote the QRE choice probabilities for player i in game G_m, and $\boldsymbol{u}_i^m \equiv \boldsymbol{u}_i^m([\boldsymbol{\pi}^*]^m)$ the corresponding equilibrium expected payoffs. Then the cyclic monotonicity property says that

$$\sum_{m=0}^{\mathcal{L}-1} \left\langle [\boldsymbol{u}_i]^{m+1} - [\boldsymbol{u}_i]^m, [\boldsymbol{\pi}_i^*]^m \right\rangle \leq 0 \tag{3}$$

for all finite game cycles[4] of length $\mathcal{L} \geq 2$, and all players i.[5] Expanding the inner product notation, the cyclic monotonicity conditions may be written as follows:

$$\sum_{m=0}^{\mathcal{L}-1} \sum_{j=1}^{J_i} \left(u_{ij}^{m+1} - u_{ij}^m \right) [\pi^*_{ij}]^m \leq 0 \tag{4}$$

This property only holds under the invariance assumption.

The number of all finite game cycles times the number of players can be, admittedly, very large. To reduce it, we note that the cyclic monotonicity conditions (4) are invariant

[4] A *cycle* of length $\mathcal{L}$ is just a sequence of $\mathcal{L}$ games $G_0, \ldots, G_{\mathcal{L}-2}, G_{\mathcal{L}-1}$ with $G_{\mathcal{L}-1} = G_0$.

[5] Under convexity of $\varphi(\cdot)$, we have $\varphi(\boldsymbol{u}_i^{m+1}) \geq \varphi(\boldsymbol{u}_i^m) + \left\langle \nabla\varphi(\boldsymbol{u}_i^m), (\boldsymbol{u}_i^{m+1} - \boldsymbol{u}_i^m) \right\rangle$. Substituting in $\nabla\varphi(\boldsymbol{u}_i^m) = \boldsymbol{\pi}_i^m$ and summing across a cycle, we obtain the CM inequality in Eq. (3).

under circular permutations of game cycles; for instance, the inequalities emerging from the cycles $G_i, \ldots, G_j, G_k, G_i$ and $G_j, \ldots, G_k, G_i, G_j$ are the same.

Two Remarks. [1] When each player's strategy set has only two pure strategies, the cycle monotonicity conditions (4) only need to be checked for cycles of length 2. Because many experiments study games where players' strategy sets consist of two elements, this observation turns out to be useful from an applied perspective.[6]

[2] What do violations of these CM inequalities pick up? Recall from the earlier discussion that QRE is a "noisy" version of Nash equilibrium. The games that we consider in our experimental application below have a unique (mixed-strategy) Nash equilibrium, so that the CM inequalities will be satisfied when agents' observed choice probabilities do not vary "too much" from the equilibrium choice probabilities. Indeed, the CM inequalities are exactly satisfied (with equality) at the noiseless mixed strategy Nash equilibrium. Hence, violations of the CM inequalities suggest that players' actions are not best responses to opponents' play, once "noise" has been accounted for. We will discuss the interpretation of CM inequalities violations more in subsection 6.2 below. ■

4 Moment inequalities for testing

Consistency with QRE can be tested nonparametrically from experimental data in which the same subject i is playing a series of one-shot games with the same strategy spaces such that each game is played multiple times. In this case, the experimental data allows to estimate a vector of probabilities $[\boldsymbol{\pi}_i^*]^m \in \Delta(S_i)$ for each game m in the sample, and we can compute the corresponding equilibrium expected utilities $[\boldsymbol{u}_i]^m$ (assuming risk-neutrality).

Suppose there are $M \geq 2$ different games in the sample. We assume that we are able to obtain estimates of $\hat{\boldsymbol{\pi}}_i^m$, the empirical choice frequencies, from the experimental data, for each subject i and for each game m. Thus we compute $\hat{\pi}_{ij}^m$ from K trials for subject i in game m:

$$\hat{\pi}_{ij}^m = \frac{1}{K} \sum_{k=1}^{K} \mathbb{1}_{\{i \text{ chooses } j \text{ in trial } k \text{ of game } m\}}$$

[6] Formally, this fact follows from the observation that for games with strategy sets of two actions, we can rewrite the functions $\varphi_i(u_i(\boldsymbol{\pi}))$ as $\varphi_i(u_{i1}(\boldsymbol{\pi})) = \varphi_i(u_{i1}(\boldsymbol{\pi}) - u_{i2}(\boldsymbol{\pi}), 0) + u_{i2}(\boldsymbol{\pi})$. Noting that without loss of generality we can normalize $u_{i2}(\boldsymbol{\pi})$ to be constant, we get that $\varphi_i(u(\boldsymbol{\pi}))$ is a univariate function. Using Rochet (1987, Proposition 2) we conclude that if φ_i satisfies (4) for all cycles of length 2, then (4) is also satisfied for cycles of arbitrary length $\mathcal{L} > 2$.

This will be the source of the sampling error in our econometric setup. Also, let $\hat{\boldsymbol{u}}_i^m \equiv \boldsymbol{u}_i^m(\hat{\boldsymbol{\pi}}^m)$ be the estimated equilibrium expected utilities obtained by plugging in the observed choice probabilities $\hat{\boldsymbol{\pi}}^m$ into the payoffs in game m. Then the sample moment inequalities take the following form: for all cycles of length $\mathcal{L} \in \{2, \ldots, M\}$

$$\sum_{m=0}^{\mathcal{L}-1} \sum_{j=1}^{J_i} \left(\hat{u}_{ij}^{m+1} - \hat{u}_{ij}^{m}\right) \hat{\pi}_{ij}^{m} \leq 0 \tag{5}$$

Altogether, in an n-person game we have $n \sum_{\mathcal{L}=2}^{M} \#C(\mathcal{L})$ moment inequalities, where $\#C(\mathcal{L})$ is the number of different (up to a circular permutation) cycles of length $\mathcal{L}$. These inequalities make up a necessary condition for a finite sample of games to be QRE-consistent.

Remarks. To estimate expected payoffs in our test we had to assume that players are risk-neutral. This assumption might be too strong a priori (e.g., Goeree, Holt, & Palfrey (2000) argue that risk aversion can help explain QRE inconsistencies). Notice, however, that the test itself does not depend on risk-neutrality: it only requires that we know the form of the utility function. Thus under additional assumptions about the utility, we can also investigate how risk aversion affects the test results. See section 6.2 for details.

Furthermore, even when players are risk-neutral, we compute the expected payoffs using observed choice frequencies, which may be different from true choice probabilities used in the CM conditions. It is therefore interesting to investigate the set of admissible utility indices/probability distributions for which QRE is not rejected by the CM test. We will consider these possibilities in our simulations and empirical implementation below.

Our test also assumes that for each of the games considered, there is only one unique QRE. Note that since we do not specify the distribution of the random utility shocks, this uniqueness assumption is not verifiable. Therefore, in principle, our test may wrongly reject (i.e., it is biased) against the null hypothesis that there are multiple quantal response equilibria played in the data. Several considerations make us feel that this possibility is not likely. First, in our experiments, the subjects are randomly matched across different rounds of each game, so that playing multiple equilibria in the course of an experiment would require a great deal or coordination. Second, all the games that we consider have unique Nash equilibria, when there are no QRE disturbances. Indeed, practically all of the empirical studies of experimental data utilizing the quantal response framework assume that a unique equilibrium is played in the data, so that the observed choices are drawn from a homogeneous sampling environment.[7]

Given the remarks here, our test of QRE should be considered, strictly speaking, a joint test of the QRE hypothesis along with those of risk neutrality of the subjects and unique equilibrium. ■

"Cumulative rank" test. HHK propose alternative methods of testing the QRE model based on cumulative rankings of choice probabilities across perturbed games,[8] which also imply stochastic equalities or inequalities involving estimated choice probabilities from different games. We will show here that, in fact, our CM conditions are directly related to HHK's rank-cumulative probability conditions in the special case when we only have two games (i.e. all cycles are of length 2), and under a certain non-negativity condition on utility differences between the games.

Formally, HHK consider two perturbed games with the same strategy spaces and re-order strategy indices for each player i such that

$$\tilde{u}_{i1}^1 - \tilde{u}_{i1}^0 \geq \tilde{u}_{i2}^1 - \tilde{u}_{i2}^0 \geq \ldots \geq \tilde{u}_{iJ_i}^1 - \tilde{u}_{iJ_i}^0$$

where $\tilde{u}_{ij}^m \equiv u_i(s_{ij}, \boldsymbol{\pi}_{-i}^m) - \frac{1}{J_i}\sum_{j=1}^{J_i} u_i(s_{ij}, \boldsymbol{\pi}_{-i}^m)$ for $m = 0, 1$. These inequalities can be equivalently rewritten as

$$u_{i1}^1 - u_{i1}^0 \geq u_{i2}^1 - u_{i2}^0 \geq \ldots \geq u_{iJ_i}^1 - u_{iJ_i}^0 \tag{6}$$

HHK's Theorem 2 states that given the indexing in (6) and assuming invariance (see Assumption 1), QRE consistency implies the following *cumulative rank property:*

$$\sum_{j=1}^{k} (\pi_{ij}^1 - \pi_{ij}^0) \geq 0; \quad \text{for all } k = 1, \ldots, J_i. \tag{7}$$

This property is related to our test as the following proposition demonstrates.

Proposition 1. *Let $M = 2$. If all expected utility differences in (6) are non-negative, then HHK rank cumulative condition (7) implies the CM inequalities (4). Conversely,*

[7] For this reason, our test may not be appropriate for testing for QRE using field data, which were not generated under these controlled laboratory experimental conditions. See De Paula & Tang (2012) for a test of multiple equilibria presence in the data.

[8] HHK also describe another testing approach which utilizes Block-Marschak polynomials involving choice probabilities across games with different choice sets, but this is unrelated to our approach in this paper.

(4) *implies HHK condition* (7) *(without additional assumptions on expected utility differences).*

Proof. See Appendix A.

5 Econometric implementation of the test

In this section we consider the formal econometric properties of our test. Let $\boldsymbol{\nu} \in \mathbb{R}^P$, where $P \equiv n \sum_{\mathcal{L}=2}^{M} \#C(\mathcal{L})$, and $\#C(\mathcal{L})$ is the number of different (up to a circular permutation) cycles of length $\mathcal{L}$, denote the vector of the left hand sides of the cyclic monotonicity inequalities (4), written out for all cycle lengths and all players. Namely, let us order all players and all different cycles of length $\mathcal{L}$ from 2 to M in a single ordering, and for $\ell \in \{1, \ldots, P\}$, let $\mathcal{L}(\ell)$ refer to the cycle length at coordinate number ℓ in this ordering, $m_0(\ell)$ refer to the first game in the respective cycle, and $\iota(\ell)$ refer to the corresponding player at coordinate number ℓ. Then we can write $\boldsymbol{\nu} \equiv (\nu_1, \ldots, \nu_\ell, \ldots, \nu_P)$ where each generic component ν_ℓ is given by (5), i.e.

$$\nu_\ell = \sum_{m=m_0(\ell)}^{\mathcal{L}(\ell)-1} \sum_{j=1}^{J_{\iota(\ell)}} \sum_{\boldsymbol{s_{-\iota(\ell)}}} \pi^m_{\iota(\ell)j} \left(\left(\prod_{k \in N_{-\iota(\ell)}} \pi^{m+1}_{k_{j_k}} \right) u^{m+1}_{\iota(\ell)}(s_{\iota(\ell)j}, \boldsymbol{s_{-\iota(\ell)}}) \right.$$
$$\left. - \left(\prod_{k \in N_{-\iota(\ell)}} \pi^m_{k_{j_k}} \right) u^m_{\iota(\ell)}(s_{\iota(\ell)j}, \boldsymbol{s_{-\iota(\ell)}}) \right) \tag{8}$$

Define $\boldsymbol{\mu} \equiv -\boldsymbol{\nu}$, then cyclic monotonicity is equivalent to $\boldsymbol{\mu} \geq \mathbf{0}$. Let $\hat{\boldsymbol{\mu}}$ denote the estimate of $\boldsymbol{\mu}$ from our experimental data. In our setting, the sampling error is in the choice probabilities π's. Using the Delta method, we can derive that, asymptotically (when the number of trials of each game out of a fixed set of M games goes to infinity),

$$\hat{\boldsymbol{\mu}} \overset{a}{\sim} N(\boldsymbol{\mu_0}, \Sigma) \quad \text{and} \quad \Sigma = JVJ'$$

where V denotes the variance-covariance matrix for the $Mn \times 1$-vector $\boldsymbol{\pi}$ and J denotes the $P \times Mn$ Jacobian matrix of the transformation from $\boldsymbol{\pi}$ to $\boldsymbol{\mu}$. Since $P >> Mn$, the resulting matrix Σ is singular.[9]

[9] Note also that Σ is the approximation of the *finite-sample* covariance matrix, so that the square-roots of its diagonal elements correspond to the standard errors; i.e. the elements are already "divided through" by the sample size, which accounts for the differences between the equations below and the corresponding ones in Andrews & Soares (2010).

We want to perform the hypothesis test:

$$H_0: \ \boldsymbol{\mu_0} \geq \mathbf{0} \quad vs. \quad H_1: \ \boldsymbol{\mu_0} \in \mathbb{R}^P$$

Given the large number of moment inequalities in our test (in the application, $P = 40$), we utilize the Generalized Moment Selection (GMS) procedure of Andrews & Soares (2010). Letting $\hat{\Sigma}$ denote an estimate of Σ, we define the test statistic

$$S(\hat{\mu}, \hat{\Sigma}) := \sum_{\ell=1}^{P} \left[\hat{\mu}^{\ell}/\hat{\sigma}_{\ell}\right]_{-}^{2} \tag{9}$$

where $[x]_-$ denotes $x \cdot \mathbb{1}(x < 0)$, and $\hat{\sigma}_1^2, \ldots, \hat{\sigma}_P^2$ denote the diagonal elements of $\hat{\Sigma}$. The test statistic is sum of squared violations across the moment inequalities.

The general intuition of the GMS procedure is to evaluate the asymptotic distribution of the test statistic under a sequence of null hypotheses which resemble the sample moment inequalities, and are drifting to zero. By doing this, moment inequalities which are far from binding in the sample (i.e. the elements of $\hat{\mu}$ which are $>> 0$) will not contribute to the asymptotic distribution of the test statistic, leading to a (stochastically) smaller distribution and hence smaller critical values.[10]

To obtain valid critical values for S under H_0, we use the following procedure from Andrews & Soares (2010):

1. Let $D \equiv Diag^{-1/2}(\hat{\Sigma})$ denote the diagonal matrix with elements $1/\hat{\sigma}_1, \ldots, 1/\hat{\sigma}_P$. Compute $\Omega \equiv D \cdot \hat{\Sigma} \cdot D$.

2. Compute the vector $\xi = \kappa_z^{-1} \cdot D \cdot \hat{\mu}$ which is equal to $\frac{1}{\kappa_z} \cdot \left[\frac{\hat{\mu}^1}{\hat{\sigma}_1}, \frac{\hat{\mu}^2}{\hat{\sigma}_2}, \cdots, \frac{\hat{\mu}^P}{\hat{\sigma}_P}\right]'$ where $\kappa_z = (\log z)^{1/2}$.[11] Here $z \equiv \frac{N}{4}$ is the total number of rounds of each of the four games, and N is the sample size.

3. For $r = 1, \ldots, R$, we generate $Z_r \sim N(0, \Omega)$ and compute $s_r \equiv S(Z_r + [\xi]_+, \Omega)$, where $[x]_+ = \max(x, 0)$.

4. Take the critical value $c_{1-\alpha}$ as the $(1-\alpha)$-th quantile among $\{s_1, s_2, \ldots, s_R\}$.

[10] In contrast, other inequality based testing procedure (e.g., Wolak (1989)) evaluate the asymptotic distribution of the test statistic under the "least-favorable" null hypothesis $\mu = 0$, which may lead to very large critical values and low power against alternative hypotheses of interest.

[11] Andrews & Soares (2010) mention several alternative choices for κ_z. We investigate their performance in the Monte Carlo simulations reported below.

Essentially, the asymptotic distribution of S is evaluated at the null hypothesis $[\xi]_+ \geq 0$ which, because of the normalizing sequence κ_z, is drifting towards zero. In finite samples, this will tend to increase the number of rejections, which is confirmed in our simulations, which we turn to next.

5.1 Monte Carlo simulations

As test games, we used a series of four card-matching games where each player has three choices. These games are so-called "Joker" games which have been studied in the previous experimental literature (cf. O'Neill (1987) and Brown & Rosenthal (1990)), and can be considered generalizations of the familiar "matching pennies" game in which each player calls out one of three possible cards, and the payoffs depend on whether the called-out cards match or not. Since these games will also form the basis for our laboratory experiments below, we will describe them in some detail here.

"Joker" games. In our choice of games, we had several considerations. We wanted to use simple games comparable to games from the previous literature. Moreover, we wanted our test to be sufficiently powerful. This last consideration steered us away from games for which we know that some structural QRE (in particular, the Logit QRE) performs very well so that the chance to fail the CM conditions is pretty low. Table 1 shows the payoff matrices of the four games which we used in our simulations and experiments.

Each of these games has a unique mixed-strategy equilibrium, the probabilities of which are given in bold font in the margins of the payoff matrices. Note that the four games in Table 1 differ only by Row player's payoff. Equilibrium logic, hence, dictates that the Row player's equilibrium choice probabilities never change across the four games, but that the Column player should change her mixtures to maintain the Row's indifference amongst choices.

Game 1 has all symmetric choices for each player. Here, the expected equilibrium payoff for Row is 50/3, and for Column is 70/3. Game 2 increases Row's payoff when both players match at the Joker (denoted "J"). Now Nash equilibrium requires Column to choose Joker almost two times less often than before to keep Row indifferent. Expected equilibrium payoff for Column stays the same – 70/3, while Row's expected payoff increases to 200/11.

Table 1: Four 3×3 games inspired by the Joker Game of O'Neill (1987).

Game 1 (Symmetric Joker)			1	2	J
			[**1/3**] (.325)	[**1/3**] (.308)	[**1/3**] (.367)
	1	[**1/3**] (.273)	10, 30	30, 10	10, 30
	2	[**1/3**] (.349)	30, 10	10, 30	10, 30
	J	[**1/3**] (.378)	10, 30	10, 30	30, 10
Game 2 (Low Joker)			1	2	J
			[**9/22**] (.359)	[**9/22**] (.439)	[**4/22**] (.202)
	1	[**1/3**] (.253)	10, 30	30, 10	10, 30
	2	[**1/3**] (.304)	30, 10	10, 30	10, 30
	J	[**1/3**] (.442)	10, 30	10, 30	55, 10
Game 3 (High Joker)			1	2	J
			[**4/15**] (.258)	[**4/15**] (.323)	[**7/15**] (.419)
	1	[**1/3**] (.340)	25, 30	30, 10	10, 30
	2	[**1/3**] (.464)	30, 10	25, 30	10, 30
	J	[**1/3**] (.196)	10, 30	10, 30	30, 10
Game 4 (Low 2)			1	2	J
			[**2/5**] (.487)	[**1/5**] (.147)	[**2/5**] (.366)
	1	[**1/3**] (.473)	20, 30	30, 10	10, 30
	2	[**1/3**] (.220)	30, 10	10, 30	10, 30
	J	[**1/3**] (.307)	10, 30	10, 30	30, 10

Notes. For each game, the unique Nash equilibrium choice probabilities are given in bold font within brackets, while the probabilities in regular font within parentheses are aggregate choice probabilities from our experimental data, described in Section 6.1.

Game 3 increases Row's payoffs when players match at 1 or 2, compared to Game 1. Now, in a Nash equilibrium, Column must play the Joker almost 50% of the time to keep Row indifferent. The expected equilibrium payoff for Column stays the same – 70/3, while Row's expected payoff increases up to 58/3. In Games 1–3, the strategies 1 and 2 are played with the same probability by Column. Game 4 introduces some asymmetry between 1 and 2, making strategies 1 and J equivalent for Column, and raises Row's payoff to 20 when both match at 1. These changes do not affect Column's expected equilibrium payoffs, while Row's expected payoff rises to 18. Thus this set of games allows for a rich set of predictions, both in terms of equilibrium choice probabilities and in terms of equivalence of pairs of strategies for Column.

Monte Carlo simulations. For the Monte Carlo simulations, we first considered artificial data generated under the QRE hypothesis. Table 2 shows the results of the GMS test procedure applied to our setup in terms of the number of rejections. From Table 2, we see that the test tends to (slightly) underreject under the QRE null for most values of the tuning parameter κ_z. The results appear relatively robust to changes in κ_z; a reasonable choice appears to be $\kappa_z = 5(\log(z))^{\frac{1}{4}}$. In a second set of simulations, we generated artificial data under non-QRE play (specifically, we generated a set of choice probabilities that generate violations of all of the CM inequalities for both players). The results here are quite stark: in all our simulations, and for all the tuning parameters that we tried, we find that the QRE hypothesis is rejected in every single replication. Thus our proposed test appears to have very good power properties.

Table 2: Monte Carlo simulation results under QRE-consistent data

		Tuning parameter κ_z			
N	# rejected[a] at	$5(\log(z))^{\frac{1}{2}}$	$5(\log(z))^{\frac{1}{4}}$	$5(\log(z))^{\frac{1}{8}}$	$5(2\log\log(z))^{\frac{1}{2}}$
1000	95%	7	9	13	7
	90%	13	17	26	14
	80%	33	54	68	46
5000	95%	13	32	43	21
	90%	26	55	77	41
	80%	61	102	124	85
9000	95%	18	40	51	32
	90%	33	61	79	53
	80%	65	114	143	97

Notes. $z = \frac{N}{4}$ is the total number of rounds of each of the four games. All numbers in columns 3–6 are observed rejections out of 500 replications. All computations use $R = 1000$ to simulate the corresponding critical values.
[a]: # rejected out of 500 replications.

6 Experimental evidence

In this section we describe an empirical application of our test to data generated from laboratory experiments. Lab experiments appear ideal for our test because the invariance of the distribution of utility shocks across games (Assumption 1) may be more likely to hold in a controlled lab setting than in the field.

Our testing procedure can be applied to the experimental data from Games 1–4 as follows. As defined previously, let the P-dimensional vector $\boldsymbol{\nu}$ contain the value of the CM inequalities evaluated at the choice frequencies observed in the experimental data. Using our four games, we can construct cycles of length $2, 3$, and 4. Thus we have 12 possible orderings of 2-cycles, 24 possible orderings of 3-cycles, and 24 possible orderings of 4-cycles. Since CM inequalities are invariant to circular permutations, it is sufficient to consider the following 20 cycles of Games $1 - 4$:

$$
\begin{aligned}
&121, 131, 141, 232, 242, 343 \\
&1231, 1241, 1321, 1341, 1421, 1431, 2342, 2432 \\
&12341, 12431, 13241, 13421, 14231, 14321
\end{aligned} \tag{10}
$$

Moreover, these 20 cycles are distinct depending on whether we are considering the actions facing the row or column player (which involve different payoffs); thus the total number of cycles across the four games and the two player roles is $P = 40$. This is the number of coordinates of vector $\boldsymbol{\nu}$, defined in (8). Additional details on the implementation of the test, including explicit expressions for the variance-covariance matrix of ν, are provided in Appendix B.

6.1 Experimental design

The subjects in our laboratory experiments were undergraduate students at the University of California, Irvine, and all experiments were conducted at the ESSL lab there. We conducted 3 sessions where subjects played, in different sequences, either some or all of the four games in Table 1. Subjects played the following sequences of games: 12, 23, and 3412. In the first two sessions, subjects played 20 rounds per game; in the last session subjects played 10 rounds per game. To reduce repeated game effects, subjects were randomly rematched each round. To reduce framing effects, the payoffs for every subject were displayed as "row player" payoffs, and actions were abstractly labelled A, B, and C for the row player, and D, E, and F for the column player.

In addition to recording the actual choice frequencies in each round of the game, we periodically also asked the subjects to report their beliefs regarding the likelihood of their current opponent playing each of the three strategies. Each subject was asked this question once s/he had chosen her action but before the results of the game were displayed. To simplify exposition, we used a two-thumb slider which allowed subjects to easily adjust the probability distribution among three choices. Thus we were able to compare the CM tests based on subjective probability estimates with the ones based on actual choices.[12]

[12]We chose not to incentivize belief elicitation rounds largely to avoid imposing extra complexity on the subjects. Thus our results using elicited belief estimates should be taken with some caution. On the other hand, if what we elicited was completely meaningless, we would not observe as much QRE

The complete instructions of the experiment are provided in Appendix C.

6.2 Experiment results

We start analyzing the experimental data by reporting the aggregate choice frequencies in Games 1–4 in Table 1 alongside Nash equilibrium predictions. Comparing theory with the data, we see that there is a lot of deviations from Nash for both column and row players.

Table 3 is our main results table. It shows the test results of checking the cyclic monotonicity conditions with our experimental data.

Based on our current dataset, we find that QRE is soundly rejected for the pooled data (with test statistic 68.194 and 95% critical value 29.985). This may not be too surprising, since in our design subjects experience both player roles (row and column), and so this pooled test imposes the auxiliary assumption on all subjects being homogeneous across roles in that their utility shocks are drawn from identical distributions.

Therefore, in the remaining portion of Table 3, we test the QRE hypothesis separately for different subsamples of the data. First, we consider separately the CM inequalities pertaining to row players and those pertaining to column players.[13] By doing this, we allow the utility shock distributions to differ depending on a subject's role (but conditional on role, to still be identical across subjects).

We find that while we still reject QRE[14] for the row players, we cannot do so for column players. Thus overall QRE-inconsistency is largely due to the behavior of the row players. Seeing that row players' inequalities are violated more often than column players' inequalities suggests that row players do not appear to be best responding to their opponents. That the violations come predominantly from the choices of row players is interesting because, as we discussed above, the column players' payoffs are the same across all the games in our experiment, but vary across games for the row player.

consistency as we do in our subject-by-subject results below.

[13]Note that the sum of the test statistics corresponding to the column and row inequalities sum up to the overall test statistic; this is because the row and column inequalities are just subsets of the full set of inequalities.

[14]Strictly speaking, this is no longer a test of QRE, because by restricting attention to cycles pertaining to only one player role, we essentially consider only one-player equilibrium version of QRE, which is more akin to a discrete choice problem.

Table 3: Testing for Cyclic Monotonicity in Experimental Data: Generalized Moment Selection

Data sample	AS **test stat**	$c^R_{0.95}$
All subjects pooled:		
All cycles	68.194	29.985
Row cycles	68.194	26.265
Col cycles	0.000	6.835

Subject-by-subject:	**Avg** AS	**Avg** $c^R_{0.95}$	**# rejected** at 95%	at 90%	at 80%	**Avg CM violations** (% of total)
Subj. v. self[a]						
(Total subj.: 96)						
All cycles	212.570	18.538	29	37	41	41.59
Row cycles	203.108	12.421	20	26	31	44.53
Column cycles	9.462	11.849	18	19	21	38.65
Subj. v. others[b]						
(Total subj.: 96)						
Row cycles	3.936	10.920	7	11	15	35.00
(Total subj.: 96)						
Col cycles	103.872	11.734	16	18	22	38.70
Subj. v. beliefs[c]						
(Total subj.: 59)						
Row cycles	3.681	6.883	5	5	5	33.051
(Total subj.: 61)						
Col cycles	9.622	8.732	10	13	14	35.000

Notes. All computations use $R = 1,000$. In subject-by-subject computations some subjects in some roles exhibited zero choice variance, so in those cases we replaced the corresponding (ill-defined) elements of $Diag^{-1/2}(\hat{\Sigma})$ with ones and when computing the test statistic, left out the corresponding components of $\hat{\mu}$. The tuning parameter in AS procedure was set equal to $\kappa_z = 5(\log(z))^{\frac{1}{4}}$.

[a] v. self: the opponent's choice frequencies are obtained from the same subject playing the respective opponent's role.

[b] v. others: the opponent's choice frequencies are averages over the subject's actual opponents' choices when the subject was playing her respective role in column (ii).

[c] v. beliefs: the opponent's choice frequencies are averages over the subject's elicited beliefs about the opponent choices when the subject was playing the respective role (since belief elicitation rounds were fixed at the session level, subjects' beliefs may not be elicited in some roles and some games. We dropped them from the analysis).

Continuing in this vein, the lower panel of Table 3 considers tests of the QRE hypothesis for each subject individually. Obviously, this allows the distributions of the utility shocks to differ across subjects. For these subject-by-subject tests, there is a question about how to determine a given's subject beliefs about his opponents' play. We consider three alternatives: (i) set beliefs about opponents equal to the subject's own play in the opponent's role; (ii) set beliefs about opponents equal to opponents' actual play (i.e., as if the subject was playing against an average opponent); and (iii) set beliefs about opponents equal to the subject's elicited beliefs regarding the opponents' play.

The results appear largely robust across these three alternative ways of setting subjects' beliefs. We see that we are not able to reject the QRE hypothesis for most of the subjects, for significance levels going from 80% to 95%. When we further break down each subject's observations depending on his/her role (as column or row player), thus allowing the utility shock distributions to differ not only across subjects but also for each subject in each role, the number of rejections decreases even more. Curiously, we see that in the subject vs. self results, the row inequalities generate more violations, while the column inequalities generate more violations in the subject vs. others results.

One caveat here, is that when we are testing on a subject-by-subject basis, we are, strictly speaking, no longer testing an equilibrium hypothesis, because we are not testing – and indeed, *cannot* test given the randomized pairing of subjects in the experiments – whether the given subject's opponents are playing optimally according to a QRE. Hence, our tests should be interpreted as tests of subjects' "best response" behavior given beliefs about how their opponents' play.

The general trend of these findings – that the QRE hypothesis appears more statistically plausible once we allow for sufficient heterogeneity across subjects and across roles – confirms existing results in McKelvey, Palfrey, & Weber (2000) who, within the parametric logit QRE framework and asymmetric matching pennies, also found evidence increasing for the QRE hypothesis once subject-level heterogeneity was accommodated.

Robustness check: Nonlinear utility and risk aversion. Our test results above are computed under the assumption of risk-neutrality. Goeree, Holt, & Palfrey (2000) have shown that allowing for nonlinear utility (i.e. risk aversion) greatly improves the fit of QRE to experimental evidence. Since our test can be applied under quite general specification of payoff functions, to see the effects of risk aversion on the test results we recomputed our test under an alternative assumption that for each player, utility from a payoff of x is $u(x) = x^{1-r}$, where $r \in [0, 1)$ is a constant relative risk aversion factor.[15] Here, we computed the test statistics and critical values for values of r ranging from 0 to 0.99.

When we pool all the subjects together, we find results very similar to what is reported in Table 3: QRE is rejected when all cycles are considered; it is also rejected when only the row cycles are considered; it cannot be rejected when only the column cycles are considered, for all values of $r \in [0, 0.99]$. Thus we do not observe any risk effects in the pooled data.[16]

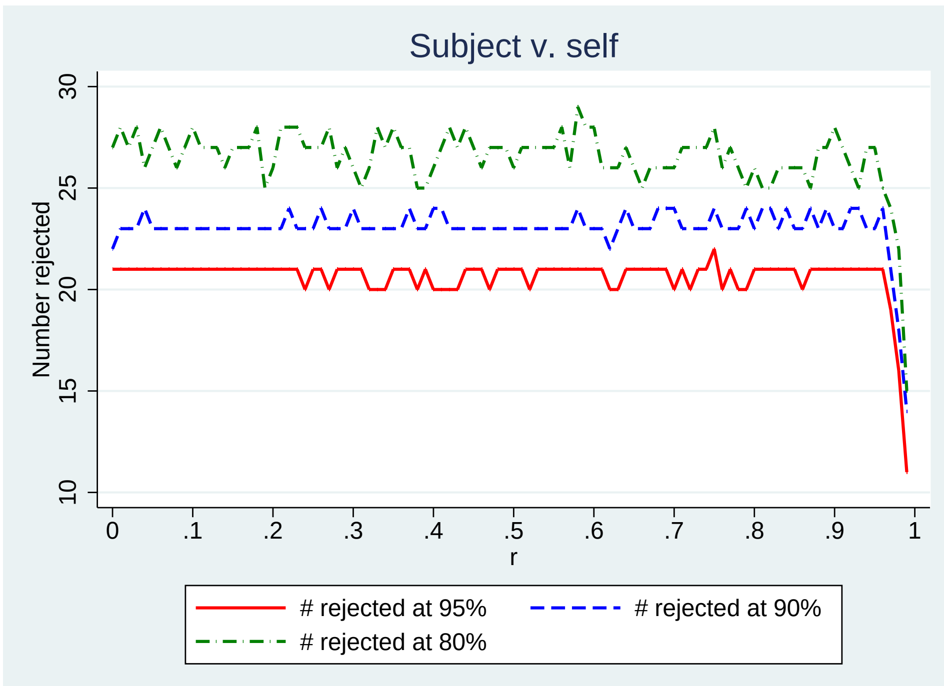

Figure 1: Effects of risk aversion on subject-by-subject rejections

Breaking down these data on a subject-by-subject basis, we once again see that allowing for risk aversion does not change our previous results obtained under the assumption of linear utility. Specifically, as graphed in Figure 1, the number of rejections of the QRE hypothesis for the "subject vs. self" specification is relatively stable for all $r < 0.99$, staying at about 21 rejections at 95% level, at about 23 rejections at 90% level, and between 25 and 30 rejections at 80% level. Thus our analysis here suggests the our test results are not driven by risk aversion.

[15]For $r = 1$ the log-utility form is used. In our computations, we restrict the largest value of r to 0.99 to avoid dealing with this issue.

[16]For space reasons, we have not reported all the test statistics and critical values, but they are available from the authors upon request.

More generally, risk aversion might be an important factor in other games, so checking for the potential effects of risk aversion on test results might be a necessary post-estimation step.

7 Conclusions and Extensions

In this paper we present a new approach for testing the QRE hypothesis in finite normal form games. The testing approach is based on moment inequalities derived from the *cyclic monotonicity* condition, which is in turn derived from the convexity of the random utility model underlying the QRE hypothesis. We investigate the performance of our test using a lab experiment where subjects play a series of generalized matching pennies games.

While we primarily focus on developing a test of the QRE hypothesis in games involving two or more players, our procedure can also be applied to situations of stochastic individual choice. Thus our test can be viewed more generally as a semiparametric test of quantal response, and, in particular, discrete choice models. Moreover, in finite action games as considered here, QRE has an identical structure to Bayesian Nash equilibria in discrete games of incomplete information which have been considered in the empirical industrial organization literature (e.g. Bajari et al. (2010), De Paula & Tang (2012), or Liu, Vuong, and Xu (2013)). Our approach can potentially be useful for specification testing in those settings; however, as we remarked above, one hurdle to implementing such tests on field data is the possibility of multiple equilibria. Adapting these tests to allow for multiple equilibria is a challenging avenue for future research.

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Appendix A Proof of Proposition 1

Suppose there are two games that differ only in the payoffs. For $M = 2$, the cyclic monotonicity condition (4) reduces to

$$\sum_{j=1}^{J_i}(u_{ij}^1 - u_{ij}^0)\pi_{ij}^0 + \sum_{j=1}^{J_i}(u_{ij}^0 - u_{ij}^1)\pi_{ij}^1 \leq 0$$

or, equivalently,

$$\sum_{j=1}^{J_i}(u_{ij}^1 - u_{ij}^0)(\pi_{ij}^0 - \pi_{ij}^1) \leq 0 \tag{11}$$

Suppose that the RHS of (6) is non-negative. Then HHK condition (7) implies CM. To see this, notice that for non-negative utilities differences in (6)

$$(u_{i1}^1 - u_{i1}^0)(\pi_{i1}^0 - \pi_{i1}^1) \leq 0$$

by HHK condition for $k = 1$. Then

$$\begin{aligned}(u_{i2}^1 - u_{i2}^0)(\pi_{i2}^0 - \pi_{i2}^1) + (u_{i1}^1 - u_{i1}^0)(\pi_{i1}^0 - \pi_{i1}^1) &\leq \\ (u_{i2}^1 - u_{i2}^0)(\pi_{i2}^0 - \pi_{i2}^1) + (u_{i2}^1 - u_{i2}^0)(\pi_{i1}^0 - \pi_{i1}^1) &= \\ (u_{i2}^1 - u_{i2}^0)((\pi_{i1}^0 + \pi_{i2}^0) - (\pi_{i1}^1 + \pi_{i2}^1)) &\leq 0\end{aligned}$$

where the last inequality follows from HHK condition for $k = 2$ and $u_{i2}^1 - u_{i2}^0 \geq 0$. Repeating the same procedure for $k = 3, \ldots, J_i$, we obtain the CM condition (11) for $M = 2$.

Conversely, suppose that (11) holds. For the case of two games, (11) holding for all players is necessary and sufficient to generate QRE-consistent choices. All premises are satisfied for HHK's Theorem 2, so condition (7) follows. One can also show it directly. Clearly, given (11), we can always re-label strategy indices so that (6) holds. Let $k = 1$ and by way of contradiction, suppose that (7) is violated, i.e.

$$\pi_{i1}^1 - \pi_{i1}^0 < 0$$

Since (11) holds, the probabilities in both games are generated by a QRE. Due to indexing in (6),

$$u_{i1}^1 - u_{ij}^1 \geq u_{i1}^0 - u_{ij}^0$$

for all $j > 1$. But then by definition of QRE in (1), $\pi_{i1}^1 \geq \pi_{i1}^0$. Contradiction, so (7) holds for $k = 1$. By induction on the strategy index, one can show that (7) holds for all $k \in \{1, \ldots, J_i\}$. This completes the proof.

Appendix B Additional details in computation of test statistic and sampling distribution

As defined in the main text, the P-dimensional vector $\boldsymbol{\nu}$ contains the value of the CM inequalities evaluated at the choice frequencies observed in the experimental data. Specifically, the ℓ-th component of $\boldsymbol{\nu}$, corresponding to a given cycle $G_0, \ldots, G_{\mathcal{L}}$ of games is given by

$$\begin{aligned}
\nu_\ell = \sum_{m=G_0}^{G_{\mathcal{L}}} & \pi_{i1}^m \left[\pi_{k1}^{m+1} u_i^{m+1}(s_{i1}, s_{k1}) - \pi_{k1}^m u_i^m(s_{i1}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{i1}, s_{k2}) - \pi_{k2}^m u_i^m(s_{i1}, s_{k2})\right. \\
& + \left.(1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{i1}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{i1}, s_{kJ})\right] \\
& + \pi_{i2}^m \left[\pi_{k1}^{m+1} u_i^{m+1}(s_{i2}, s_{k1}) - \pi_{k1}^m u_i^m(s_{i2}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{i2}, s_{k2}) - \pi_{k2}^m u_i^m(s_{i2}, s_{k2})\right. \\
& + \left.(1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{i2}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{i2}, s_{kJ})\right] \\
& + (1 - \pi_{i1}^m - \pi_{i2}^m) \left[\pi_{k1}^{m+1} u_i^{m+1}(s_{iJ}, s_{k1}) - \pi_{k1}^m u_i^m(s_{iJ}, s_{k1})\right. \\
& + \pi_{k2}^{m+1} u_i^{m+1}(s_{iJ}, s_{k2}) - \pi_{k2}^m u_i^m(s_{iJ}, s_{k2}) \\
& + \left.(1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{iJ}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{iJ}, s_{kJ})\right]
\end{aligned}$$

where we use i to denote the row player, k to denote the column player, and ℓ changes from 1 to 20. For the column player and $\ell \in [21, 40]$ the analogous expression is as follows:

$$\begin{aligned}
\nu_\ell = \sum_{m=G_0}^{G_{\mathcal{L}}} & \pi_{k1}^m \left[\pi_{i1}^{m+1} u_k^{m+1}(s_{i1}, s_{k1}) - \pi_{i1}^m u_k^m(s_{i1}, s_{k1}) + \pi_{i2}^{m+1} u_k^{m+1}(s_{i2}, s_{k1}) - \pi_{i2}^m u_k^m(s_{i2}, s_{k1})\right. \\
& + \left.(1 - \pi_{i1}^{m+1} - \pi_{i2}^{m+1}) u_k^{m+1}(s_{iJ}, s_{k1}) - (1 - \pi_{i1}^m - \pi_{i2}^m) u_k^m(s_{iJ}, s_{k1})\right] \\
& + \pi_{k2}^m \left[\pi_{i1}^{m+1} u_k^{m+1}(s_{i1}, s_{k2}) - \pi_{i1}^m u_k^m(s_{i1}, s_{k2}) + \pi_{i2}^{m+1} u_k^{m+1}(s_{i2}, s_{k2}) - \pi_{i2}^m u_k^m(s_{i2}, s_{k2})\right. \\
& + \left.(1 - \pi_{i1}^{m+1} - \pi_{i2}^{m+1}) u_k^{m+1}(s_{iJ}, s_{k2}) - (1 - \pi_{i1}^m - \pi_{i2}^m) u_k^m(s_{iJ}, s_{k2})\right] \\
& + (1 - \pi_{k1}^m - \pi_{k2}^m) \left[\pi_{i1}^{m+1} u_k^{m+1}(s_{i1}, s_{kJ}) - \pi_{i1}^m u_k^m(s_{i1}, s_{kJ})\right. \\
& + \pi_{i2}^{m+1} u_k^{m+1}(s_{i2}, s_{kJ}) - \pi_{i2}^m u_k^m(s_{i2}, s_{kJ}) \\
& + \left.(1 - \pi_{i1}^{m+1} - \pi_{i2}^{m+1}) u_k^{m+1}(s_{iJ}, s_{kJ}) - (1 - \pi_{i1}^m - \pi_{i2}^m) u_k^m(s_{iJ}, s_{kJ})\right]
\end{aligned}$$

We differentiate the above expressions with respect to π^m to obtain a $P \times 16$ estimate of the Jacobian $\hat{J} = \frac{\partial}{\partial \boldsymbol{\pi}} \boldsymbol{\mu}(\hat{\boldsymbol{\pi}})$ in order to compute an estimate of the variance-covariance matrix $\hat{\Sigma}_{[P \times P]} = \hat{J} \hat{V} \hat{J}'$ by the Delta method.

For the case of four games, the partial derivatives form the 40×16 matrix $\hat{J}$. The first 20 rows correspond to the differentiated LHS of the cycles for the row player, and the last 20 rows correspond to the differentiated LHS of the cycles for the column player. The first 8 columns correspond to the derivatives with respect to π_{i1}^m, π_{i2}^m, and the last 8 columns correspond to the derivatives with respect to π_{k1}^m, π_{k2}^m, $m \in \{1, \ldots, 4\}$.[17]

[17] Clearly, the probability to choose Joker can be expressed via the probabilities to choose 1 and 2, using the total probability constraint.

Let $S_0^m \equiv \{\ell \in \{1,\ldots,40\} | m \notin C_\ell\}$ be the set of cycle indices such that corresponding cycles (in the order given in (10)) do not include game m. E.g., for $m = 1$, $S_0^m = \{4,5,6,13,14,24,25,26,33,34\}$. Let $S_i^m \equiv \{\ell \in \{1,\ldots,20\} | \ell \notin S_0^m\}$ be a subset of cycle indices that include game m and pertain to the row player, and let $S_k^m \equiv \{\ell \in \{21,\ldots,40\} | \ell \notin S_0^m\}$ be a subset of cycle indices that include game m and pertain to the column player. Finally, for a cycle of length $\mathcal{L}$, denote $\ominus \equiv - \mod \mathcal{L}$ subtraction modulus $\mathcal{L}$.

We can now express the derivatives with respect to π_{i1}^m and π_{i2}^m, $m \in \{1,\ldots,4\}$, in the following general form. The partial derivatives wrt π_{i1}^m are

$$
\begin{aligned}
\frac{\partial \nu_\ell}{\partial \pi_{i1}^m} &= 0 && \text{for } \ell \in S_0^m \\
\frac{\partial \nu_\ell}{\partial \pi_{i1}^m} &= \pi_{k1}^{m+1} u_i^{m+1}(s_{i1}, s_{k1}) - \pi_{k1}^m u_i^m(s_{i1}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{i1}, s_{k2}) \\
&\quad - \pi_{k2}^m u_i^m(s_{i1}, s_{k2}) + (1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{i1}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{i1}, s_{kJ}) \\
&\quad - \big[\pi_{k1}^{m+1} u_i^{m+1}(s_{iJ}, s_{k1}) - \pi_{k1}^m u_i^m(s_{iJ}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{iJ}, s_{k2}) - \pi_{k2}^m u_i^m(s_{iJ}, s_{k2}) \\
&\quad + (1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{iJ}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{iJ}, s_{kJ})\big] && \text{for } \ell \in S_i^m \\
\frac{\partial \nu_\ell}{\partial \pi_{i1}^m} &= \pi_{k1}^m \left[-u_k^m(s_{i1}, s_{k1}) + u_k^m(s_{iJ}, s_{k1})\right] + \pi_{k2}^m \left[-u_k^m(s_{i1}, s_{k2}) + u_k^m(s_{iJ}, s_{k2})\right] \\
&\quad + (1 - \pi_{k1}^m - \pi_{k2}^m) \left[-u_k^m(s_{i1}, s_{kJ}) + u_k^m(s_{iJ}, s_{kJ})\right] \\
&\quad + \pi_{k1}^{m\ominus 1} \left[u_k^m(s_{i1}, s_{k1}) - u_k^m(s_{iJ}, s_{k1})\right] + \pi_{k2}^{m\ominus 1} \left[u_k^m(s_{i1}, s_{k2}) - u_k^m(s_{iJ}, s_{k2})\right] \\
&\quad + (1 - \pi_{k1}^{m\ominus 1} - \pi_{k2}^{m\ominus 1}) \left[u_k^m(s_{i1}, s_{kJ}) - u_k^m(s_{iJ}, s_{kJ})\right] && \text{for } \ell \in S_k^m
\end{aligned}
$$

The partial derivatives wrt π_{i2}^m are

$$
\begin{aligned}
\frac{\partial \nu_\ell}{\partial \pi_{i2}^m} &= 0 && \text{for } \ell \in S_0^m \\
\frac{\partial \nu_\ell}{\partial \pi_{i2}^m} &= \big[\pi_{k1}^{m+1} u_i^{m+1}(s_{i2}, s_{k1}) - \pi_{k1}^m u_i^m(s_{i2}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{i2}, s_{k2}) - \pi_{k2}^m u_i^m(s_{i2}, s_{k2}) \\
&\quad + (1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{i2}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{i2}, s_{kJ})\big] \\
&\quad - \big[\pi_{k1}^{m+1} u_i^{m+1}(s_{iJ}, s_{k1}) - \pi_{k1}^m u_i^m(s_{iJ}, s_{k1}) + \pi_{k2}^{m+1} u_i^{m+1}(s_{iJ}, s_{k2}) - \pi_{k2}^m u_i^m(s_{iJ}, s_{k2}) \\
&\quad + (1 - \pi_{k1}^{m+1} - \pi_{k2}^{m+1}) u_i^{m+1}(s_{iJ}, s_{kJ}) - (1 - \pi_{k1}^m - \pi_{k2}^m) u_i^m(s_{iJ}, s_{kJ})\big] && \text{for } \ell \in S_i^m \\
\frac{\partial \nu_\ell}{\partial \pi_{i2}^m} &= \pi_{k1}^m \left[-u_k^m(s_{i2}, s_{k1}) + u_k^m(s_{iJ}, s_{k1})\right] + \pi_{k2}^m \left[-u_k^m(s_{i2}, s_{k2}) + u_k^m(s_{iJ}, s_{k2})\right] \\
&\quad + (1 - \pi_{k1}^m - \pi_{k2}^m) \left[-u_k^m(s_{i2}, s_{kJ}) + u_k^m(s_{iJ}, s_{kJ})\right] \\
&\quad + \pi_{k1}^{m\ominus 1} \left[u_k^m(s_{i2}, s_{k1}) - u_k^m(s_{iJ}, s_{k1})\right] + \pi_{k2}^{m\ominus 1} \left[u_k^m(s_{i2}, s_{k2}) - u_k^m(s_{iJ}, s_{k2})\right] \\
&\quad + (1 - \pi_{k1}^{m\ominus 1} - \pi_{k2}^{m\ominus 1}) \left[u_k^m(s_{i2}, s_{kJ}) - u_k^m(s_{iJ}, s_{kJ})\right] && \text{for } \ell \in S_k^m
\end{aligned}
$$

To obtain the derivatives with respect to π_{k1}^m and π_{k2}^m, one just needs to use the corresponding partial derivatives wrt π_{i1}^m and π_{i2}^m, and exchange everywhere the subscripts i and k, so we omit the derivation. For the sake of completenes, though, we list the indices subsets for each game $m \in \{1,..,4\}$ in Table 4.

Table 4: Sets of cycle indices for each game.

m	S_0^m	S_i^m	S_k^m
1	4, 5, 6, 13, 14, 24, 25, 26, 33, 34	1, 2, 3, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20	21, 22, 23, 27, 28, 29, 30, 31, 32, 35, 36, 37, 38, 39, 40
2	2, 3, 6, 10, 12, 22, 23, 26, 30, 32	1, 4, 5, 7, 8, 9, 11, 13, 14, 15, 16, 17, 18, 19, 20	21, 24, 25, 27, 28, 29, 31, 33, 34, 35, 36, 37, 38, 39, 40
3	1, 3, 5, 8, 11, 21, 23, 25, 28, 31	2, 4, 6, 7, 9, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20	22, 24, 26, 27, 29, 30, 32, 33, 34, 35, 36, 37, 38, 39, 40
4	1, 2, 4, 7, 9 21, 22, 24, 27, 29	3, 5, 6, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	23, 25, 26, 28, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40

Notes. The cycle indices are for the row player. To obtain the corresponding column player cycle indices, swap the last two columns.

Appendix C Experiment Instructions

The instructions in the experiment, given below, largely follow McKelvey, Palfrey, & Weber (2000).

This is an experiment in decision making, and you will be paid for your participation in cash. Different subjects may earn different amounts. What you earn depends partly on your decisions and partly on the decisions of others.

The entire experiment will take place through computer terminals, and all interaction between subjects will take place through the computers. It is important that you do not talk or in any way try to communicate with other subjects during the experiment. If you violate the rules, we may ask you to leave the experiment.

We will start with a brief instruction period. If you have any questions during the instruction period, raise your hand and your question will be answered so everyone can hear. If any difficulties arise after the experiment has begun, raise your hand, and an experimenter will come and assist you.

This experiment consists of several periods or matches and will take between 30 to 60 minutes. I will now describe what occurs in each match.

[Turn on the projector]

First, you will be randomly paired with another subject, and each of you will simultaneously be asked to make a choice.

Each subject in each pair will be asked to choose one of the three rows in the table which will appear on the computer screen, and which is also shown now on the screen at the front of the room. Your choices will be always displayed as rows of this table, while your partner's choices will be displayed as columns. It will be the other way round for your partner: for them, your choices will be displayed as columns, and their choices as rows.

You can choose the first, the second, or the third row. Neither you nor your partner will be informed of what choice the other has made until after all choices have been made.

After each subject has made his or her choice, payoffs for the match are determined based on the choices made. Payoffs to you are indicated by the red numbers in the table, while payoffs to your partner are indicated by the blue numbers. Each cell represents a pair of payoffs from your choice and the choice of your partner. The units are in francs, which will be exchanged to US dollars at the end of the experiment.

For example, if you choose 'A' and your partner chooses 'D', you receive a payoff of 10 francs, while your partner receives a payoff of 20 francs. If you choose 'A' and your partner chooses 'F', you receive a payoff of 30 francs, while your partner receives a payoff of 30 francs. If you choose 'C' and your partner chooses 'E', you receive a payoff of 10 francs, while your partner receives a payoff of 20 francs. And so on.

Once all choices have been made the resulting payoffs and choices are displayed, the history panel is updated and the match is completed.

[show the slide with a completed match]

This process will be repeated for several matches. The end of the experiment will be announced without warning. In every match, you will be randomly paired with a new subject. The identity of the person you are paired with will never be revealed to you. The payoffs and the labels may change every match.

After some matches, we will ask you to indicate what you think is the likelihood that your current partner has made a particular choice. This is what it looks like.

[show slide with belief elicitation]

Suppose you think that your partner has a 15% chance of choosing 'D' and a 60% chance of choosing 'E'. Indicate your opinion using the slider, and then press 'Confirm'. Once all subjects have indicated their opinions and confirmed them, the resulting payoffs and choices are displayed, the history panel is updated and the match is completed as usual.

Your final earnings for the experiment will be the sum of your payoffs from all matches. This amount in francs will be exchanged into U.S. dollars using the exchange rate of 90 cents for 100 francs. You will see your total payoff in dollars at the end of the experiment. You will also receive a show-up fee of $7. Are there any questions about the procedure?

[wait for response]

We will now start with four practice matches. Your payoffs from the practice matches are not counted in your total. In the first three matches you will be asked to choose one of the three rows of a table. In the fourth match you will be also asked to indicate your opinion about the likelihood of your partner's choices for each of three actions. Is everyone ready?

[wait for response]

Now please double click on the 'Client Multistage' icon on your desktop. The program will ask you to type in your name. Please type in the number of your computer station instead.

[wait for subjects to connect to server]

We will now start the practice matches. Do not hit any keys or click the mouse button until you are told to do so.

[start first practice match]

You see the experiment screen. In the middle of the screen is the table which you have previously seen up on the screen at the front of the room. At the top of the screen, you see your subject ID number, and your computer name. You also see the history panel which is currently empty.

We will now start the first practice match. Remember, do not hit any keys or click the mouse buttons until you are told to do so. You are all now paired with someone from this class and asked to choose one of the three rows. Exactly half of your see label 'A' at the left hand side of the top row, while the remaining half now see label 'D' at the same row.

Now, all of you please move the mouse so that it is pointing to the top row. You will see that the row is highlighted in red. Move the mouse to the bottom row and the highlighting goes along with the mouse. To choose a row you just click on it. Now please click once anywhere on the bottom row.

[Wait for subjects to move mouse to appropriate row]

After all subjects have confirmed their choices, the match is over. The outcome of this match, 'C'-'F', is now highlighted on everybody's screen. Also, note that the moves and payoffs of the match are recorded in the history panel. The outcomes of all of your previous matches will be recorded there throughout the experiment so that you can refer back to previous outcomes whenever you like. The payoff to the subject who chose 'C' for this match is 20, and the payoff to the subject who chose F is '10'.

You are not being paid for the practice session, but if this were the actual experiment, then the payoff you see on the screen would be money (in francs) you have earned from the first match. The total you earn over all real matches, in addition to the show-up fee, is what you will be paid for your participation in the experiment.

We will now proceed to the second practice match.

[Start second match]

For the second match, you have been randomly paired with a different subject. You are not paired with the same person you were paired with in the first match. The rules for the second match are exactly like for the first. Please make your choices.

[Wait for subjects]

We will now proceed to the third practice match. The rules for the third match are exactly like the first. Please make your choices.

[Start third match]

We will now proceed to the fourth practice match. The rules for the fourth match are exactly like the first. Please make your choices.

[Wait for subjects]

Now that you have made your choice, you see that a slider appears asking you to indicate the relative likelihood of your partner choosing each of the available actions. There is also a confirmation button. Please indicate your opinion by adjusting the thumbs and then press 'Confirm'.

[wait for subjects]

This is the end of the practice match. Are there any questions?

[wait for response]

Now let's start the actual experiment. If there are any problems from this point on, raise your hand and an experimenter will come and assist you. Please pull up the dividers between your cubicles.

[start the actual session]

The experiment is now completed. Thank you all very much for participating in this experiment. Please record your total payoff from the matches in U.S. dollars at the experiment record sheet. Please add your show-up fee and write down the total, rounded up to the nearest dollar. After you are done with this, please remain seated. You will be called by your computer name and paid in the office at the back of the room one at a time. Please bring all your things with you when you go to the back office. You can leave the experiment through the back door of the office.

Please refrain from discussing this experiment while you are waiting to receive payment so that privacy regarding individual choices and payoffs may be maintained.