

Changing Preferences: An Experiment and Estimation of Market-Incentive Effects on Altruism

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Abstract

This paper studies how altruistic preferences are changed by markets and incentives. We conduct a laboratory experiment in a within-subject design. Subjects are asked to choose health care qualities for hypothetical patients in monopoly, duopoly, and quadropoly. Prices, costs, and patient benefits are experimental incentive parameters. In monopoly, subjects choose quality to tradeoff between profits and altruistic patient benefits. In duopoly and quadropoly, we model subjects playing a simultaneous-move game. Each subject is uncertain about an opponent's altruism, and competes for patients by choosing qualities. Bayes-Nash equilibria describe subjects' quality decisions as functions of altruism. Using a nonparametric method, we estimate the population altruism distributions from Bayes-Nash equilibrium qualities in different markets and incentive configurations. Markets tend to reduce altruism, although duopoly and quadropoly equilibrium qualities are much higher than those in monopoly. Although markets crowd out altruism, the disciplinary powers of market competition are stronger. Counterfactuals confirm markets change preferences.

Keywords: preferences, altruism, markets, incentives

JEL: C14, C57, C72

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1 Introduction

Recent economic research has questioned the monolithic power of incentives and markets. Economists now legitimately question if more competition or high-powered incentives must result in more outputs or worker efforts. A multifaceted approach has been advanced. Economic agents' preferences may include more than utility from financial reward and disutility from cost or effort. In fact, economic agents may be fair minded, altruistic, and socially responsible, but may also be spiteful.

Clearly, social and individual preferences determine behaviors and market outcomes. The usual research methodology says that given multi-dimensional preferences, economists can write analytical and empirical models to study incentives and markets. A deeper question, of course, is what determines social preferences. There, economists often concede that anthropologists, sociologists, psychologists, and neuroscientists may have identified plausible factors such as climate, cultural-historical events, physiology, and genetics to explain preferences. But when these factors remain exogenous, the usual methodology remains valid.

In this paper, we assess whether social preferences can be changed by markets and incentives, the key social institutions that economists study. Our focus is on altruism, market competition, and incentives.¹ This paper presents experimental evidence that altruistic preferences can be diminished by competition and altered by incentives. In other words, economic models that analyze altruism's effect on market and incentives must confront the possibility that markets and incentives themselves may change altruism.

Our research proceeds in three steps. First, we use a structural model to decompose behavioral changes into preference effects and market-incentive effects. This is the key conceptual step. Behavioral outcomes are interactions between preferences and market-incentive institutions.² Must altruistic preferences remain immutable when markets and incentives change? Our structural model allows altruistic preferences to be

¹We use the term altruism to mean a decision maker's enjoyment when his action in a game benefits others who are outside of the game. This has been called pure altruism in the literature (see, for example, Andreoni 1989, 1990). By contrast, a broader notion of altruism would allow a decision maker also to gain enjoyment from actions performed by his rivals in the same game. This notion of global altruism, which involves social norm or peer effect, is not our focus.

²A few recent papers have made claims that markets do erode morality or social responsibility, but our view is simply that the decomposition is the key. The recent papers fall short of this; more details are in the literature review subsection.

influenced by markets and incentives. Behavioral changes are then results of markets and incentives changing preferences as well as equilibria.

Second, we use a laboratory experiment in which incentives and market competition are exogenously varied for subjects. Identifying preference and market-incentive effects by real data is too daunting a task. A controlled environment offers a better chance. Our experimental framing is health care provision, and subjects are primed to be altruistic. They choose health care qualities which affect their own payoffs and which benefit patients through a transfer to a charity for the treatment of ophthalmic patients outside the laboratory. We also have taken care to isolate subjects, so such confounding factors as fairness, collusion, and spitefulness could be minimized. Each subject experiences different markets and incentive configurations. Our within-subject design is appropriate because we claim that preferences change, not just that preferences are heterogenous (which could be identified by a between-subject design).

Third, we adapt the nonparametric econometric method by Guerre, Perrigne and Vuong (2000) to estimate preference distributions. We estimate subjects' altruism distributions separately as subjects experience different markets and different incentive configurations. The nonparametric method does not restrict us to prespecified distribution classes, and is straightforward to implement.

We show that subjects become less altruistic when they have to compete against others in a duopoly or in a quadropoly, compared to when they are monopolists. The flip side is that when subjects become monopolists, they become more altruistic. Our contribution can be likened to the classic Lucas critique in policy evaluations. Given preferences, equilibrium outcomes result from market-incentive institutions. This common view is inadequate: preferences are not given. The structure of an economic model consists of equilibrium decisions based on economic agents' preferences. When preferences vary systematically with changes in the market-incentive environment, rather than remaining exogenous, a change in the market-incentive environment will systematically alter the structure of the economic model.

For the theoretical model, we specify that a subject's preferences are given by a weighted average of patients' benefits from health care quality, and profits. By choosing a higher quality, the subject reduces profit, but raises patient benefits. A more altruistic subject puts a higher weight on patients' benefits. The

tradeoff between benefits and profits depend on three experimental parameters: a subject's price (revenue) per patient, quality cost, and patient benefit.

A subject makes decisions in three markets: monopoly, duopoly, and quadropoly. Under monopoly a subject chooses the quality for the entire patient population. Under duopoly and quadropoly, subjects move simultaneously and each subject's market share depends on the entire profile of subjects' quality choices, according to a logistic demand function. A total of 361 subjects participated in experimental sessions in October 2017 and April 2018 at the University of Cologne. Within each of the three markets, we systematically vary the incentives using a $2 \times 2 \times 2$ factorial design. Price, cost, and patient benefit assume binary values for a total of eight incentive configurations. In total, each subject played 24 games.

Each basic game is one of incomplete information: a player's altruism is his own private information, but each is uncertain about another player's altruism. We assume that the uncertainty on altruism is described by a distribution. It is this distribution that we would estimate, for each market and for each incentive configuration. The estimation is by means of symmetric Bayes-Nash equilibria.

Nonparametric estimation yield very different altruism distributions for the 24 games. The striking pattern is that for each incentive configuration, estimated altruism distributions exhibit lower means in duopoly relative to monopoly, and yet even lower means in quadropoly. Subjects have become less altruistic and value profits more when the market becomes more competitive. What is more striking, however, is that the observed equilibrium qualities are much higher in duopoly and quadropoly than monopoly. Although subjects have become less altruistic, the competition disciplinary force is stronger.

These results offer a deeper interpretation than the usual, reduced-form approach. If only behavioral results are considered, then markets and incentives are shown to raise qualities, so one would conclude that there is no crowding out. We reject the simplistic conclusion. In fact, quality changes result from two effects: preference changes, and market-incentive changes. The effects go in opposite directions. Markets reduce altruism, but also discipline subjects. In our experiment, the market-incentive effect is stronger than the preference-change effect. Together they produce the observed behavioral results. Our structural approach permits counter factual calculations. It also allows straightforward robustness checks.

It has not escaped our notice that the ultimate questions are: why has competition, according to our evidence, diminished altruism, and why has the competitive disciplinary effect turned out to be stronger? These questions, perhaps, strike a counterpoint to the usual exogenous assumptions for analysis of economic models. Recent advances in neuroscience have adopted a reductionist principle that all behaviors can be traced to electrochemical activities in the brain. We are neither in any position to render an opinion nor did we manage to use brain scans to assess if competition triggered specific neural activities. However, we can speculate. When subjects play monopoly, they only have to consider a tradeoff between profits and patient benefits. When subjects play duopoly, they are presented with an additional concern: the competitor's quality choice. The tradeoff between profits and patient benefits now depends on what the rival subject would choose. Complexity has increased, and perhaps the higher cognitive demand has diluted the concern for patient benefits.

The plan of the paper is as follows. The next subsection is a literature review. The model is set up in Section 2. The experimental design and sessions are described in Section 3. In Section 4, we present quality choice descriptive statistics, the nonparametric estimator, and then estimation results on altruism. We also perform nonparametric tests on the equality of the estimated altruism distributions. We end the section with some counterfactual quality estimations. Section 5 presents the reduced-form analysis. The last section draws some conclusion. Appendix A contains experiment materials. Appendix B contains robustness checks. We consider an alternate utility function, and a between-subject subsample.

1.1 Literature review

Our paper is related to three strands in the literature. First, we relate to the growing body of work on the impact of markets on moral and prosocial behaviors. Evidence from laboratory experiments in such framing and contexts as altruistic motives, free-riding, and social responsibility indicates that competition reduces moral behavior.

Falk and Szech (2013) show that repeated interactions in bilateral and multilateral free-offer markets reduce morals compared to individual decisions. Subjects are more willing to accept a negative externality imposed on a third-party (a mouse getting killed) in markets. Using a consumer and firms in a laboratory

experiment, Bartling, Weber, and Yao (2015) analyze socially responsible behavior in posted-price markets. They find evidence for socially responsible behaviors in markets, but such behaviors are stronger in non-market contexts. In a follow-up study, Bartling, Valero, and Weber (2017) report similar patterns for different externalities. Kirchler et al. (2015) analyze how trading anonymity, involvement with the traded good, and punishment influence moral behavior in a double auction with negative externalities imposed on third parties (voiding measles vaccine donations). Building on Kirchler et al. (2015), Sutter et al. (2016) report that moral behaviors are consistent with lower trading volume in markets with negative externalities, but externalities do not affect market prices.

The literature aims to show that social preferences may be altered by the market structure. Shifts in preferences are typically inferred from observed behaviors. In single-person decision environments, this seems a natural inference. However, we consider a multi-person strategic interaction environment. Therefore, behaviors are equilibrium outcomes, which in turn depend on preferences and the market structure. Hence, our use of a structural model to identify changes in altruistic preferences is necessary to decompose behavioral changes into those due to preferences and strategic changes. Bartling, Weber, and Yao (2015) also employ a structural modelling approach. They estimate consumers' preferences by a conditional logit choice model. Whereas they show that the average buyer cares for a third-party's earnings, preferences are assumed to remain unchanged in different market treatments. However, in their setup, consumers simply make purchase decisions after firms have chosen products and prices, so do not engage in a strategic game against firms.

Further, the above studies use a between-subject design. Instead, we use a within-subject design to identify preferences changes. Also, we examine a (regulated) market in which economic agents on the supply-side compete for market share by benefiting third parties. We do not let subjects do harm to third parties.³ Neither do we let subjects receive feedbacks about their decisions, so learning, reputation, and peer effects are well controlled; for further discussion, see Bartling, Weber and Yao (2015) and Breyer and Weimann (2015). Furthermore, we change competition and incentives one at a time, so the confounding effects of multiple changes between manipulations can be avoided.

³A prominent example in which social preferences are an important concern for supply side's behavior is markets for public services (e.g., Besley and Ghatak, 2005) and credence goods (e.g., Dulleck and Kerschbamer, 2006; Dulleck, Kerschbamer, and Sutter, 2011), and health care (e.g., Arrow, 1963).

Our study relates to the literature on prosocial behavior, incentives, and crowding-out. Ultimatum, dictator, public good, trust, and gift-exchange game experiments analyze behavioral changes due to incentives; see Bowles and Polania-Reyes (2012) for a summary. Economic incentives are often found to reduce prosocial behaviors. Experimental evidence tends to confirm crowding out; see, for example, Falk and Kosfeld (2006), Gneezy and Rustichini (2000a, b), and Mellström and Johannesson (2008). Our paper points to the inadequacy of identifying crowding out only in terms of outcomes. Incentive schemes are disciplinary, even when they may erode social motives. The missing link is that market-incentive mechanisms and social motives pull in different directions, and it is an empirical matter which is stronger.

Finally, our nonparametric estimation relates to the literature on structurally estimating preferences. This literature has been on measuring inequity aversion and reciprocity (e.g., Charness and Rabin, 2002; Bellemare, Kröger, and van Soest, 2008), and altruism (e.g., Andreoni, 1989; Andreoni and Miller, 2002; Fisman, Kariv, and Markovits, 2007); see DellaVigna (2018) for a summary. Using data from field experiments, a few papers structurally infer social preferences to identify differences between charitable giving and worker effort; see DellaVigna, List, and Malmendier (2012) and DellaVigna et al. (2016). We, however, use a nonparametric estimator developed by Guerre, Perrigne and Vuong (2000) that has originated from estimating Bayes-Nash equilibria in first-price auctions. We have used the monotonicity of qualities in altruism for identification; this is similar to identification by the monotonicity of auction bids in valuations in Guerre, Perrigne and Vuong (2000).

2 A model of altruism and competition

The experiment frames subjects to provide medical services at some quality to a set of patients.⁴ We study three market games: monopoly, duopoly, and quadropoly. The monopoly game is a single-person decision problem, and the simultaneous-move duopoly and quadropoly games are strategic problems.

⁴There were no real patients in the laboratory, and the subjects were not medical doctors. We operationalized the quality of medical services by converting it to actual cash payments that benefited real patients outside of the laboratory. See footnote 5 and the end of Subsection 3.1.

2.1 Demand

In each market, there are 100 patients. Under monopoly, each subject simply makes the quality decision, q between 0 and 10, for all the 100 patients. In duopoly and quadropoly, subjects choose qualities simultaneously. Then the subjects' quality profile determines each subject's market share according to a logistic demand system. For duopoly, let q_1 and q_2 be qualities chosen by subject 1 and subject 2. The numbers of patients for subjects 1 and 2 are, respectively,

$$\frac{100 \exp(bq_1)}{\exp(bq_1) + \exp(bq_2)} \quad \text{and} \quad \frac{100 \exp(bq_2)}{\exp(bq_1) + \exp(bq_2)}, \quad (1)$$

where $b > 0$ is a patient-benefit parameter. For quadropoly, let q_1, q_2, q_3 , and q_4 denote the four subjects' quality choices. Subject i who chooses quality q_i will have

$$\frac{100 \exp(bq_i)}{\exp(bq_1) + \exp(bq_2) + \exp(bq_3) + \exp(bq_4)} \quad (2)$$

patients. The logistic demand guarantees that each subject gets some patients under any quality profile, and is commonly used for discrete-choice situations when consumers' utilities may be subject to Type I Extreme Value disturbances.

2.2 Quality choices and preferences

A subject receives a fixed payment $p > 0$ for each patient that he treats. For the theoretical model, a subject's quality choice is a continuous variable between 0 and 10 (although in the experiment we set the possible qualities to be integers between 0 and 10, a total of 11 choices). The subject bears the per-patient quality cost at cq^2 when he provides medical service at quality q , where $c > 0$ is a cost parameter. Medical service at quality q gives a benefit bq to a patient. We call the environment defined by the three parameters, payment p , cost c , and patient benefit b , an *incentive configuration*.

Our health care framing primes an experiment subject for an altruistic motive when qualities are chosen. We assume that a subject's preferences are represented by $\alpha bq + U(p - cq^2)$, for some parameter α and an increasing and concave function U , so preferences are linear combinations of the patient benefit bq , and the utility of his own profit $U(p - cq^2)$. We maintain the assumption that a subject earns altruistic utility from

his own patients. (We will discuss “global” altruism, in which a subject values all patient benefits, in the next Subsection.) Framing and priming affect subjects differently, so we assume that the preference weight on patient benefit, α , is a random variable on an interval $[\underline{\alpha}, \bar{\alpha}] \subset \mathbb{R}$ with some distribution.

2.3 Monopoly, duopoly and quadropoly

In monopoly, each subject simply chooses a quality for his 100 patients. If a subject’s altruism parameter is α and he chooses quality q , the subject’s per-patient payoff is $\alpha bq + U(p - cq^2)$. A profit-maximizing subject (whose α is set at 0) chooses $q = 0$, whereas a subject who only cares about patient benefit chooses the maximum quality, which is 10. Otherwise, a subject’s “interior” optimal quality is given by the first-order condition:

$$\alpha b - U'(p - cq^2) \times 2cq = 0. \quad (3)$$

In monopoly, altruism is the only reason behind a subject choosing a strictly positive quality. In fact, the first-order condition (3) defines a monotone relationship between α and the optimal quality:

$$\alpha = \frac{2cq}{b} U'(p - cq^2). \quad (4)$$

A more altruistic subject is willing to forgo more profit for a higher quality for patients. Given a utility function U , equation (4) allows us to infer the value of α from subjects’ quality choices.

The experiment subjects also play the duopoly and quadropoly games. We will lay out all the details in duopoly, but we will be rather succinct in quadropoly. In duopoly, two subjects are randomly paired. They simultaneously choose qualities, say q_1 and q_2 , which result in market shares in (1). The subjects’ payoffs are

$$[\alpha_1 bq_1 + U(p - cq_1^2)] \times \frac{100 \exp(bq_1)}{\exp(bq_1) + \exp(bq_2)} \quad \text{and} \quad [\alpha_2 bq_2 + U(p - cq_2^2)] \times \frac{100 \exp(bq_2)}{\exp(bq_1) + \exp(bq_2)},$$

where α_1 and α_2 are the subjects’ altruism parameters.

We model duopoly as a Bayesian game. We assume that each subject’ altruism parameter, α , is drawn independently from a random variable with distribution F and density f on support $[\underline{\alpha}, \bar{\alpha}]$. Each subject observes his own altruism parameter, but not an opponent’s altruism parameter. The uncertainty on the

altruism parameter α is the basis for the Bayesian perspective, and stems from framing having different effects on different subjects.

A subject's strategy in the duopoly game is a function that maps the altruism parameter α to a quality, say, $q : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$. If subject 1 has altruism parameter α_1 and chooses q_1 when the rival subject 2 follows a strategy $q' : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$, subject 1's expected utility is

$$\begin{aligned} \text{EU}(q_1; q') &= \int_{\underline{\alpha}}^{\bar{\alpha}} \left\{ [\alpha_1 b q_1 + U(p - cq_1^2)] \left[\frac{100 \exp(bq_1)}{\exp(bq_1) + \exp(bq'(x))} \right] \right\} dF(x) \\ &= [\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} \left[\frac{100 \exp(bq_1)}{\exp(bq_1) + \exp(bq'(x))} \right] dF(x). \end{aligned} \quad (5)$$

We assume that a subject does not earn any utility from patient benefits provided by a rival subject. The expression in (5) only concerns those patients the subject serves. An alternate form of "global" altruism, which includes patient benefits the rival subject provides is outside our current consideration. A first reason is tractability; Bayes-Nash equilibria will be more complicated, and the estimation of the equilibria would become difficult. Second, global altruism will inevitably involve some concern about free riding, and some notion about peer effect of quality provision, which we have chosen to suppress. The suppression of concern other than private altruism will be discussed in the experimental design section.

The market share is defined by

$$S(q_1; q') \equiv \frac{\exp(bq_1)}{\exp(bq_1) + \exp(bq')},$$

so we can rewrite the expected utility in (5) as

$$\text{EU}(q_1; q') = [\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100 S(q_1; q'(x)) dF(x). \quad (6)$$

The market share term is the difference between monopoly and duopoly. A subject choosing a higher quality earns a higher market share:

$$\frac{dS(q_1; q')}{dq_1} = bS(q_1; q')[1 - S(q_1; q')] > 0$$

In duopoly, even a purely profit-maximizing subject ($\alpha = 0$) has an incentive to offer quality because a higher quality gains market share which generates profits.

For each value of $\alpha_1 \in [\underline{\alpha}, \bar{\alpha}]$, we let

$$q(\alpha_1; q') = \operatorname{argmax}_{q_1} [\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100S(q_1; q'(x)) dF(x) \quad (7)$$

be subject 1's best response against the rival's strategy $q'(\alpha) : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$. A subject's optimal quality choice is still a tradeoff between profit and patient benefit. However, a subject's payoff depends on what he believes about his rival subject's qualities, which are chosen according to the strategy q' . A symmetric Bayes-Nash equilibrium strategy specifies a subject's quality choice for each value of the altruism parameter that maximizes the subject's expected utility, given that the rival subject uses the same strategy.

Definition 1 (Duopoly Bayes-Nash Equilibrium) *The strategy $q^* : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$ is a symmetric Bayes-Nash equilibrium, if, at each $\alpha \in [\underline{\alpha}, \bar{\alpha}]$,*

$$q^*(\alpha) = \operatorname{argmax}_q [\alpha b q + U(p - cq^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100S(q; q^*(x)) dF(x). \quad (8)$$

The usual characterization of an equilibrium is by means of the first-order condition for the maximization of (6) or the best response in (7). Given a rival's strategy q' , for the maximization of expected utility in (6), we obtain the first-order derivative with respect to q_1 :

$$\begin{aligned} \frac{\partial \text{EU}(q_1; q')}{\partial q_1} &= [\alpha_1 b - 2cq_1 U'(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100S(q_1; q'(x)) dF(x) \\ &\quad + [\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100bS(q_1; q'(x)) [1 - S(q_1; q'(x))] dF(x). \end{aligned} \quad (9)$$

We assume that the expected utility in (6) is quasi-concave for the incentive configurations under consideration. Hence, by setting the first-order derivative to zero, we obtain the implicit function that defines the best response at α .

To characterize the symmetric Bayes-Nash equilibrium $q^* : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$, we note that at the equilibrium, each subject has the same first-order condition. The equilibrium q^* therefore is defined by the equation from setting (9) to 0 at each $\alpha \in [\underline{\alpha}, \bar{\alpha}]$ with q' set to q^* :

$$\begin{aligned} &[\alpha b - 2cq^*(\alpha)U'(p - cq^*(\alpha)^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100S(q^*(\alpha); q^*(x)) dF(x) \\ &+ [\alpha b q^*(\alpha) + U(p - cq^*(\alpha)^2)] \times \int_{\underline{\alpha}}^{\bar{\alpha}} 100bS(q^*(\alpha); q^*(x)) [1 - S(q^*(\alpha); q^*(x))] dF(x) = 0. \end{aligned} \quad (10)$$

Being the solution of an integral equation, a symmetric Bayes-Nash equilibrium is difficult to compute, even for simple functional forms of the utility U and distribution F . Fortunately, we do not have to rely on this computation. In fact, what makes our model operational is the following.

Lemma 1 *Equilibrium strategy $q^* : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$ is monotone increasing in α .*

Proof of Lemma 1: Using the first-order derivative of EU with respect to q_1 in (9), we further differentiate this with respect to α_1 to obtain

$$\frac{\partial^2 \text{EU}(q_1; q')}{\partial \alpha_1 \partial q_1} = b \int_{\underline{\alpha}}^{\bar{\alpha}} 100S(q_1; q'(x))dF(x) + bq_1 \int_{\underline{\alpha}}^{\bar{\alpha}} 100bS(q_1; q'(x))[1 - S(q_1; q'(x))]dF(x) > 0.$$

By assumption EU is quasi-concave in q_1 , so as α_1 increases, the optimal quality increases. This is true for any given strategy q' , so remains valid at the equilibrium q^* . ■

Because α is a random variable, the equilibrium strategy $q^*(\alpha)$ is also a random variable. An equilibrium duopoly is the pair of qualities specified by the equilibrium strategy, $(q^*(\alpha_1), q^*(\alpha_2))$, for two independent realizations of α , namely α_1 for the first subject, and α_2 for the second subject.

Remark 1 (Duopoly Equilibrium Quality Distribution) *The Bayes-Nash equilibrium q^* induces a joint distribution of the two subjects' equilibrium qualities on $[0, 10] \times [0, 10]$. By symmetry and independence, the marginal density is the one induced by the equilibrium strategy q^* . Denoting this marginal distribution by $G^* : [0, 10] \rightarrow [0, 1]$, we conclude that for $\tilde{q} \in [0, 10]$, $G^*(\tilde{q}) = F(\tilde{\alpha})$, where $q^*(\tilde{\alpha}) = \tilde{q}$.*

The actual play of the duopoly are realizations of G^* . By the monotonicity of the equilibrium q^* , the distribution F of α and the equilibrium quality distribution G^* are isomorphic. Whereas we have no data on F , we do have data on qualities from equilibrium play. This is the key to the estimation of the altruism distribution F under duopoly, and Subsection 4.2 will present the estimation of G^* by the empirical quality distribution.

Next, we discuss quadropoly. There are now four subjects, and the demands are in (2). Otherwise, there is not much conceptual difference between duopoly and quadropoly. The definition of a symmetric

Bayes-Nash equilibrium has exactly the same form. If subject i chooses quality q_i , his market share now is

$$S(q_i; q_{-i}) = \frac{\exp(bq_i)}{\sum_{j=1}^4 \exp(bq_j)},$$

where we use q_{-i} to denote the quality vector (q_1, q_2, q_3, q_4) with the i^{th} element omitted. Given strategies q_j , $j = 1, 2, 3, 4$, $j \neq i$, if subject i chooses quality q_i his expected utility is

$$[\alpha_i b q_i + U(p - cq_i^2)] \times \int \int \int 100 S(q_i; q_{-i}(\alpha_{-i})) \prod_{j=1, j \neq i}^4 dK(\alpha_j),$$

where the notation $q_{-i}(\alpha_{-i})$ is a short hand for $(q_j(\alpha_j), j = 1, 2, 3, 4, j \neq i)$, and K is the distribution of α in quadropoly.

Definition 2 (Quadropoly Bayes-Nash Equilibrium) *The strategy $q^{**}(\alpha)$ is a symmetric Bayes-Nash equilibrium, if, at each $\alpha \in [\underline{\alpha}, \bar{\alpha}]$,*

$$q^{**}(\alpha) = \operatorname{argmax}_q [\alpha b q + U(p - cq^2)] \int \int \int \{100 S(q; q_{-i}^{**}(\alpha_{-i}))\} \prod_{j=1, j \neq i}^4 dK(\alpha_j). \quad (11)$$

We can use the first-order condition to characterize the equilibrium strategy q^{**} . It is straightforward to verify the same monotonicity property.

Lemma 2 *Equilibrium strategy $q^{**} : [\underline{\alpha}, \bar{\alpha}] \rightarrow [0, 10]$ is monotone increasing in α .*

Remark 2 (Quadropoly Equilibrium Quality Distribution) *The Bayes-Nash equilibrium q^{**} induces a joint distribution of the four subjects' equilibrium qualities on $[0, 10]^4$. By symmetry and independence, the marginal density is the one induced by the equilibrium strategy q^{**} . We denote this marginal distribution by $L^{**} : [0, 10] \rightarrow [0, 1]$.*

Notice that we have used the notation F to denote the altruism distribution in duopoly, but we have used a different notation K for that in quadropoly. Although we have the same set of subjects in 3 markets and 8 incentive configurations, we do allow altruism distributions to vary according to markets and incentive configurations. We now turn to the experiment.

3 The experiment

3.1 Design

The experimental design implements the theoretical model just described. Role playing as physicians, subjects decide on the quality of health care for a set of hypothetical patients.⁵ Each subject chooses a medical-service quality q from a finite set $\{0, 1, 2, \dots, 10\}$.⁶ Three parameters determine payoffs. These are the capitation payment to the physician p , the quality cost parameter c , and the patient benefit parameter, b . The subject bears the quality cost, so if he chooses a quality q , his profit becomes $p - cq^2$, whereas the patient benefit is bq , exactly the same as in the theoretical model.

We use a $2 \times 2 \times 2$ factorial design to vary each of the p , c , and b parameters systematically. The capitation payment p may be low or high, set at 10 and 15, respectively. The cost parameter c can be either 0.075 or 0.1, whereas the benefit parameter b can be either 0.5 or 1. All monetary amounts were in terms of the experimental currency, Taler, which was later converted to Euro at the rate of 100:1. A full set of parameters can be found in Table 12 in Appendix B. We call a game with a profile of price-cost-benefit parameters an incentive configuration. The $2 \times 2 \times 2$ variations set up a total of 8 incentive configurations. There are 3 markets: monopoly, duopoly, and quadropoly. Each subject plays 24 games in the entire experiment: 8 incentive configurations by 3 markets.

The experiment uses a within-subject design. Subjects experience different markets and incentive configurations, and we aim to investigate how subjects' quality choices and preferences change according to their experiences. In the actual implementation, subjects played all 8 incentive-configuration games in one market, and then moved onto the next market. Subjects were not informed of the market up until they were to play the 8 incentive-configuration games in that market.⁷

⁵Hypothetical patient profiles, characterizing patients through different benefits from medical treatment decisions, have been employed in several behavioral experiments in health with medical and non-medical students (e.g., Hennig-Schmidt, Selten, Wiesen, 2011; Kesternich, Schumacher, Winter, 2015; and Brosig-Koch et al., 2017) and practicing physicians (e.g., Brosig-Koch et al., 2016, 2019).

⁶This is the only difference from the continuous quality choice assumption in the theoretical model.

⁷It was impractical to get subjects to play the 24 games in a random order. Too much back-and-forth between markets and incentive configurations could be confusing to subjects. Random rematching for 16 times for each subject also would be too time consuming.

There are 6 different ways to order the three markets, displayed in Table 1. For example, in “3 (D-Q-M)” a subject plays the duopoly game first, followed by quadropoly, and finally monopoly. We roughly assigned about 1/6 of the subject population to each of the 6 orders. The last column in Table 1 lists the number of subjects who participated in each order. We randomize the order in which the 8 incentive configurations are presented to subjects. In each market, each subject plays the 8 games in the following order: 1st, ($p = 10$, $c = 0.1$, $b = 1$); 2nd, ($p = 10$, $c = 0.075$, $b = 1$); 3rd, ($p = 15$, $c = 0.1$, $b = 0.5$); 4th, ($p = 15$, $c = 0.1$, $b = 1$); 5th, ($p = 10$, $c = 0.1$, $b = 0.5$); 6th, ($p = 10$, $c = 0.075$, $b = 0.5$); 7th ($p = 15$, $c = 0.075$, $b = 1$) and 8th, ($p = 15$, $c = 0.075$, $b = 0.5$).

Table 1: Market orders in the experiment

Condition	Order of markets	Number of subjects
1 (M-D-Q)	Monopoly-Duopoly-Quadropoly	64
2 (M-Q-D)	Monopoly-Quadropoly-Duopoly	60
3 (D-Q-M)	Duopoly-Quadropoly-Monopoly	63
4 (Q-M-D)	Quadropoly-Monopoly-Duopoly	60
5 (Q-D-M)	Quadropoly-Duopoly-Monopoly	58
6 (D-M-Q)	Duopoly-Monopoly-Quadropoly	56
Total		361

We used the common “random-choice” payment method to determine profits and patient benefits. One of the 8 incentive-configuration games in each market would be chosen randomly for determining the subject’s profit and the patient benefits. The random-choice payment method was implemented for each subject independently.

A subject never learns others’ decisions for any of the 8 incentive-configuration games in a market. However, at the end of one market session, each subject is given a summary information of actual demands, profits, and patient benefits, aggregated over the 8 games. In duopoly and quadropoly, subjects are randomly paired or grouped. When subjects are done with one market, say duopoly, the match will be dissolved. Then subjects will be randomly matched for the next market, say quadropoly. Subjects do play a normal form game against others randomly drawn from a population.

Our design rules out repeated plays, learning, and reputation. We have thought about the design tradeoff.

On the one hand, we would like to keep altruism as the main frame, and would like to avoid issues about norms and collusions. On the other hand, we would have to face the possibility that subjects having to learn to play a Bayes-Nash equilibrium. In the end, we have come down with a design that would rely on subjects playing a Bayes-Nash equilibrium with preferences governed by altruism. This explains our suppressing information of subjects' play and outcomes. Our approach also gives supports about the rejection of global altruism. Subjects do not have information about patient benefits other than those patients he has chosen benefits for. We have maintained the altruism frame throughout. It is inappropriate to introduce a control that eliminates the patient benefits, or to make the benefits independent of subjects' quality choices.⁸

We do want to find out if subjects' preferences change according to markets and incentive configurations. Randomly assigning subjects to play different market and incentive-configuration games would identify differences, not changes. However, we can use a subsample for a between-subject design. We construct this subsample by taking data from a subject's experiences in the market he or she first participates. Given that we have 361 subjects, a between-subject design would put only about 120 subjects in one market, and each subject would then play only 8 games. The between-subject subsample serves as a comparison with the main within-subject design. The analysis is in Appendix B. Broadly, the results are consistent with the complete sample for the within-subject design.

Although there are no real patients, the health benefits accrued in the laboratory are converted into monetary transfers to a charity dedicated to providing surgeries for ophthalmic patients. The patient benefit is thus made salient. A subject's consideration of patients' benefit from costly quality choices have real empirical and health-related consequences.

3.2 Experimental sessions

Experimental sessions were carried out in October 2017 and in April 2018, at the Cologne Laboratory for Experimental Research of the University of Cologne. Subjects in the experiment were mostly students from the University of Cologne, Germany. Participants were invited via the ORSEE platform (Greiner, 2015).

⁸To eliminate patient benefit, we would have to write a new set of instructions, and let subjects see different screens in the experiments. It is questionable how such a setup could be argued as any control or variant. Besides, we would not be able to control what subjects would think about what qualities were doing.

In total, 361 subjects participated in the experiment.⁹ Subjects on average were about 24 years old, and 55% of them were female. Among the subjects who were students, 131 were in law and social sciences, 22 in medicine, 42 in arts and humanities, 49 in mathematics and natural sciences, 35 in theology. There were 21 in other disciplines or non-students; 61 subjects did not provide their faculty information.

The experiment was programmed in zTree (Fischbacher, 2007). Upon arrival, subjects were randomly assigned to cubicles. Initial instructions informed subjects that the experiment consisted of three parts. Detailed instructions of each part would only be given at the start of that part. Each part corresponded to one of the three markets (monopoly, duopoly, and quadropoly). Participants had adequate time to read the instructions. The instructions can be found in Appendix A.1. Participants were allowed to ask clarifying questions, which were answered in private. For each market, subjects needed to answer several control questions. Subjects should understand the price, cost, and benefit parameters, and how quality choices might affect demands. Each subject must answer all control questions correctly to ensure an adequate understanding before the start of each part of the experiment. The control questions can be found in Appendix A.2.

When making a decision, each subject was informed of the incentive-configuration parameters, as well as profits and the patient benefits as functions of the quality that can be one in $\{0, 1, 2, \dots, 10\}$. In monopoly, each subject had 100 patients. In duopoly and quadropoly, a subject had a logistic demand which depended on the quality profile of matched subjects. The zTree program provided a calculator, which allowed subjects to practice inputting own and other players' qualities to calculate the resultant demands (number of patients), profits, and patient benefits for all players. A screen shot of the calculator is in Appendix A.3. After subjects played the 8 incentive-configuration games in a market, they were informed of their and their paired subject's or subjects' total demands (number of patients), and total patient benefits in the 8 games. Data about individual games in each incentive configuration were not given. Our design gets each of 361 subjects to play 24 games. Subjects were not told about the market sequence in advance; this minimized the likelihood

⁹We dropped three subjects who did not complete their last, monopoly sessions due to technical problems (one subject in condition 3 (D-Q-M), and two in condition 5 (Q-D-M)). However, these three subjects did interact with other subjects before they played their last monopoly session. We have kept data of others who played against these three subjects in duopoly and quadropoly.

of their behaviors being affected by anticipation of competition.

One subject was randomly chosen to be a monitor. After the experiment, the monitor verified that a money order equal to the total patient benefit was issued by the Finance Department of the University of Cologne. The money order was payable to an organization, *Christoffel Blindenmission*, which supports ophthalmologists performing cataract surgeries in a hospital in Masvingo, Zimbabwe. The money order was sealed in an envelope, and the monitor and an experiment assistant then deposited the envelope in the nearest mailbox. The monitor was paid an additional €5. Subjects were told in advance that the experimental patient benefits would be for real patients, but not for those in a developing country to avoid motives of compassion and rather to remain in a health context. A similar procedure for making patient benefits meaningful to subjects has been applied by, for example, Hennig-Schmidt, Selten and Wiesen (2011), Kesternich, Schumacher and Winter (2015), and Brosig-Koch et al. (2017).

Sessions lasted, on average, for about 90 minutes, and subjects earned, on average, about €14.20 (€18.20 including show-up fee). The average benefit per patient was about €8.10. In total, €2,923.60 were transferred to the Christoffel Blindenmission. Average costs for a cataract operation for adults are about €30, so our experiment supported about 100 surgeries.¹⁰

4 Estimation of altruism distributions from experimental data

We first present data of subjects' quality choices. Then we describe how we estimate structurally the α altruism distribution for each market and in each incentive configuration.

4.1 Descriptive statistics on subjects' quality choices

Table 2 presents some summary statistics of the 361 subjects' quality choices in the 8 incentive-configuration games in the 3 markets. Clearly, subjects chose higher qualities in duopoly and quadropoly than in monopoly, and the standard deviations of subjects' quality choices were also much smaller. Raising the intensity of competition from duopoly to quadropoly increases qualities only slightly more. Within a market, quality

¹⁰For more on activities of the Christoffel Blindenmission related to cataract, see www.cbm.de/spendenCBM_Spenden_Sie_fuer_Operationen_am_Grauen_Star-494570.html.

variations between the 8 incentive-configuration games seem quite modest.

Table 2: Means and standard deviations of subjects' quality choices

Incentive configurations	Monopoly		Duopoly		Quadropoly	
	mean	st. dev.	mean	st. dev.	mean	st. dev.
($p = 10, c = 0.075, b = 0.5$)	4.17	2.99	7.75	1.58	8.26	1.40
($p = 10, c = 0.075, b = 1$)	4.15	2.99	7.98	1.59	8.31	1.56
($p = 10, c = 0.1, b = 0.5$)	3.79	2.79	6.94	1.35	7.34	1.34
($p = 10, c = 0.1, b = 1$)	3.73	2.80	7.09	1.52	7.46	1.34
($p = 15, c = 0.075, b = 0.5$)	4.82	3.43	8.82	1.53	9.09	1.32
($p = 15, c = 0.075, b = 1$)	4.83	3.41	8.98	1.60	9.15	1.43
($p = 15, c = 0.1, b = 0.5$)	4.51	3.27	8.19	1.63	8.55	1.47
($p = 15, c = 0.1, b = 1$)	4.44	3.19	8.40	1.62	8.65	1.61
Total	4.31	3.14	8.02	1.70	8.35	1.57

For each of the 24 games, we draw the quality histograms; they are in Figures 1 to 3, and the actual frequency of each quality between 0 and 10 is written at the top of each vertical bar. These frequencies will be used for estimating subjects' altruism parameter.

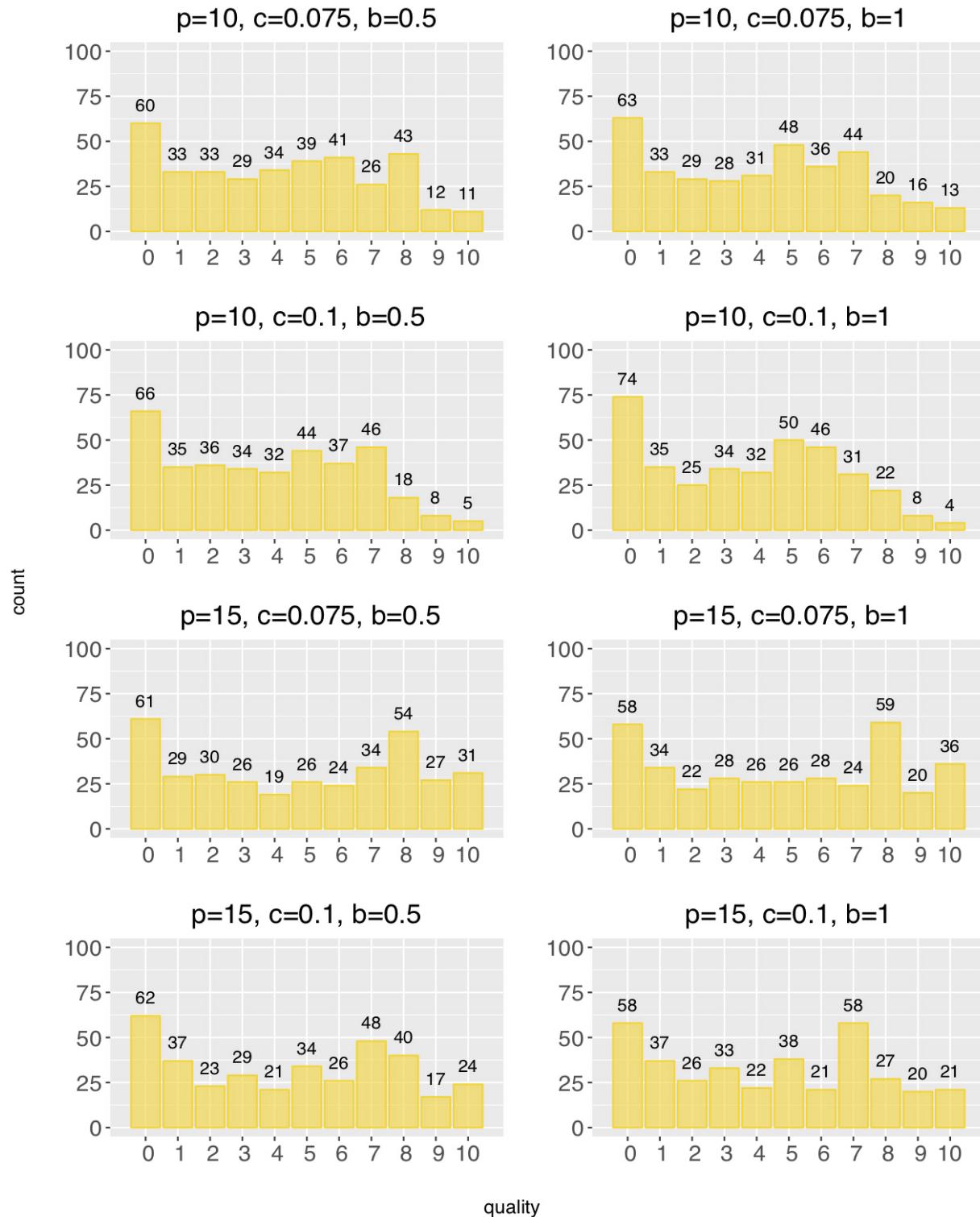


Figure 1: Quality histograms in monopoly

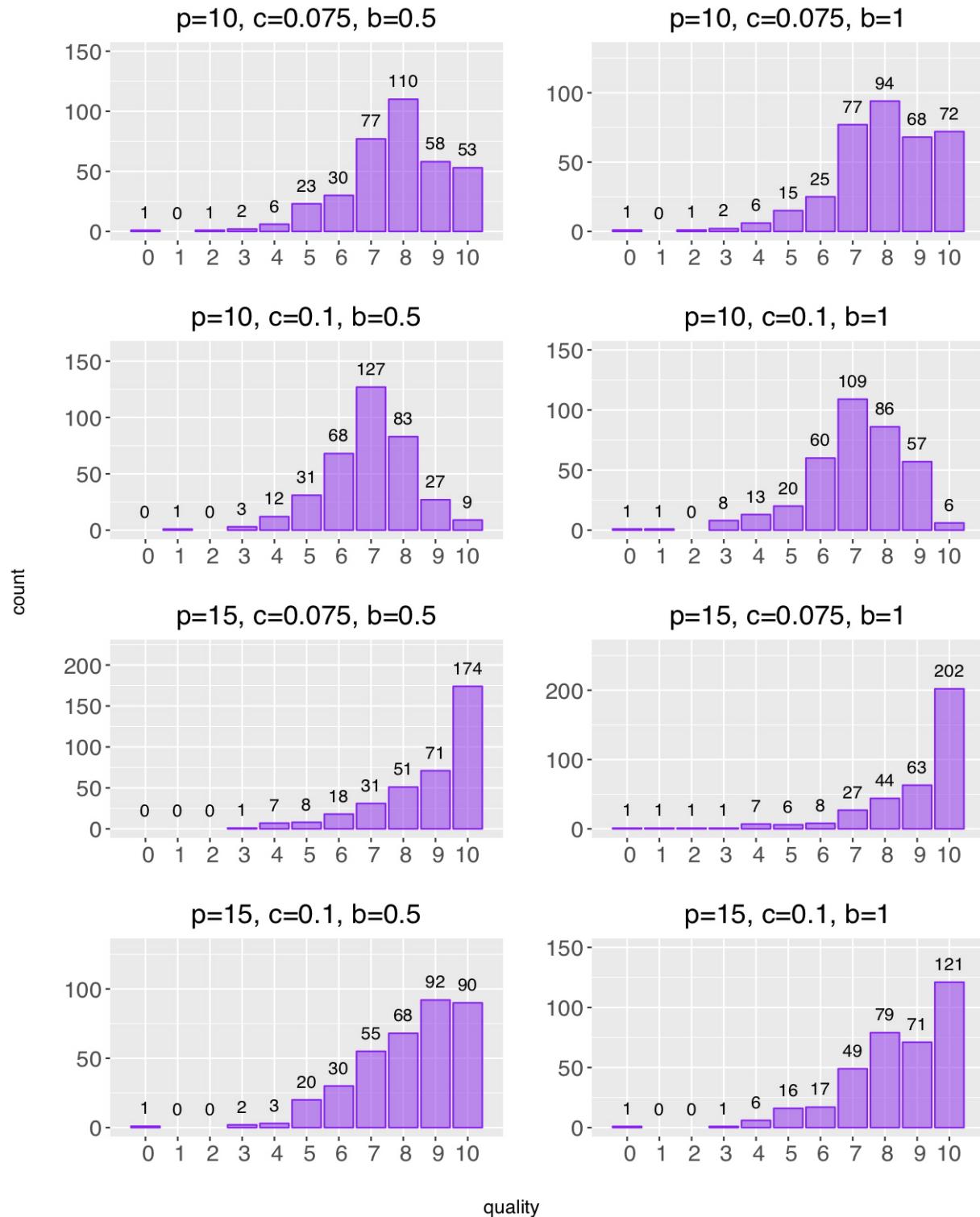


Figure 2: Quality histograms in duopoly

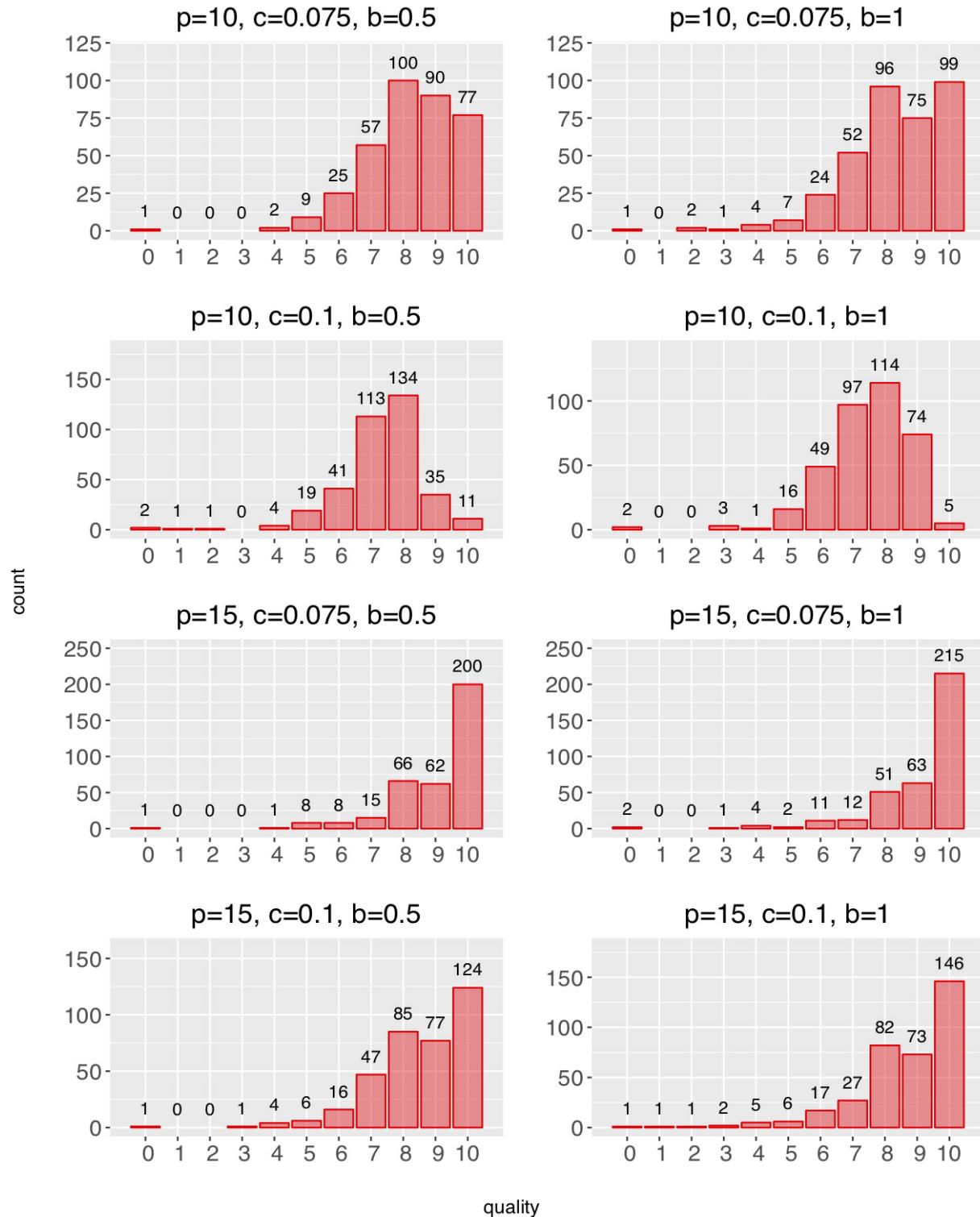


Figure 3: Quality histograms in quadropoly

Clearly, the 24 histograms show higher qualities in duopoly and quadropoly than monopoly. Nevertheless, the difference between duopoly and quadropoly does not appear to be very significant. Quality frequencies are needed for the estimation of altruism parameters, to which we now turn.

4.2 Nonparametric estimation of altruism distribution by Bayes-Nash equilibria

We adapt a nonparametric estimation method developed by Guerre, Perrigne and Vuong (2000) (abbreviated to GPV) for first-price auctions. We use duopoly to illustrate the adaptation. First, from the equilibrium strategy q^* in (10), we invert and obtain α in terms of the equilibrium quality $q^*(\alpha)$, the utility function U , and incentive parameters:

$$\alpha = \frac{\left\{ \begin{array}{l} 2cq^*(\alpha)U'(p - cq^*(\alpha)^2) \int_{\underline{\alpha}}^{\bar{\alpha}} S(q^*(\alpha); q^*(x))dF(x) \\ -U(p - cq^*(\alpha)^2) \times \int_{\underline{\alpha}}^{\bar{\alpha}} bS(q^*(\alpha); q^*(x))[1 - S(q^*(\alpha); q^*(x))]dF(x) \end{array} \right\}}{\left\{ \begin{array}{l} b \int_{\underline{\alpha}}^{\bar{\alpha}} S(q^*(\alpha); q^*(x))dF(x) \\ + bq^*(\alpha) \int_{\underline{\alpha}}^{\bar{\alpha}} bS(q^*(\alpha); q^*(x))[1 - S(q^*(\alpha); q^*(x))]dF(x) \end{array} \right\}}. \quad (12)$$

Given an equilibrium q^* , the uncertainty concerning a rival subject's altruism is equivalent to the uncertainty of the rival's quality choices. From Remark 1, we can replace the altruism distribution F by the equilibrium quality distribution G^* . Then, using q to denote the equilibrium quality chosen by the subject with altruism parameter α , we rewrite (12) as

$$\alpha = \frac{2cqU'(p - cq^2) \int_0^{10} S(q; x)dG^*(x) - U(p - cq^2) \times \int_0^{10} bS(q; x)[1 - S(q; x)]dG^*(x)}{b \int_0^{10} S(q; x)dG^*(x) + bq \int_0^{10} bS(q; x)[1 - S(q; x)]dG^*(x)}. \quad (13)$$

This says that given an equilibrium q^* , we can use the equilibrium quality distribution G^* to express a subject's altruism parameter α in terms of his quality choice q . We estimate the α distribution by recovering their values from subjects' quality choices. The estimated α is a nonlinear map of the chosen quality q , and the equilibrium quality distribution G^* , given the game's parameters.

The argument suggests that we adapt the GPV two-step method as follows. In Step 1, the densities of equilibrium quality distribution G^* are estimated by the empirical quality densities in each market-incentive-configuration constellation. Let $\hat{g}(x)$ denote the empirical quality densities; it is the fraction of subjects (out

of the total of 361) who have chosen quality $x = 0, 1, \dots, 10$. We use $\hat{g}(x)$ to estimate the G^* 's densities. The empirical densities of the 24 games are those in Figures 1 to 3.

The term $\int_0^{10} S(q; x) dG^*(x)$ in (13) is now estimated by $\sum_{x=0}^{10} S(q; x) \hat{g}(x)$; similarly, the term $\int_0^{10} bS(q; x)[1 - S(q; x)] dG^*(x)$ in (13) is estimated by $\sum_{x=0}^{10} bS(q; x)[1 - S(q; x)] \hat{g}(x)$. For each subject $i = 1, \dots, 361$, we use (13) to calculate:

$$\hat{\alpha}_i = \frac{2cq_i U'(p - cq_i^2) \sum_{x=0}^{10} S(q_i; x) \hat{g}(x) - U(p - cq_i^2) \sum_{x=0}^{10} bS(q_i; x)[1 - S(q_i; x)] \hat{g}(x)}{b \sum_{x=0}^{10} S(q_i; x) \hat{g}(x) + bq_i \sum_{x=0}^{10} bS(q_i; x)[1 - S(q_i; x)] \hat{g}(x)}, \quad (14)$$

which is an estimate of subject i 's α . In Step 2, we use the sample of estimated α 's to estimate nonparametrically the altruism distribution:

$$\hat{F}(a) = \frac{1}{361} \sum_{i=1}^{361} I\{\hat{\alpha}_i \leq a\}. \quad (15)$$

where I is the indicator function that takes the value 1 when the condition inside the curly brackets is satisfied, and 0 otherwise.

The estimation procedures are similar for monopoly and quadropoly. In monopoly, we use the first-order condition (4) to recover a subject's α value from his quality choice in any given incentive-market configuration. In other words, in the first step, for each $i = 1, \dots, 361$, we compute

$$\hat{\alpha}_i = \frac{2cq_i U'(p - cq_i^2)}{b}.$$

Then these estimated α 's are used to estimate the distribution of altruism in the second step.

For quadropoly, in the first step, we compute the following

$$\hat{\alpha}_i = \frac{2cq_i U'(p - cq_i^2) \sum_{x,y,z=0}^{10} S(q_i; x, y, z) \hat{l}(x) \hat{l}(y) \hat{l}(z) - U(p - cq_i^2) \sum_{x,y,z=0}^{10} bS(q_i; x, y, z)[1 - S(q_i; x, y, z)] \hat{l}(x) \hat{l}(y) \hat{l}(z)}{b \sum_{x,y,z=0}^{10} S(q_i; x, y, z) \hat{l}(x) \hat{l}(y) \hat{l}(z) + bq_i \sum_{x,y,z=0}^{10} bS(q_i; x, y, z)[1 - S(q_i; x, y, z)] \hat{l}(x) \hat{l}(y) \hat{l}(z)},$$

where $\hat{l}(x)$, $x = 0, 1, \dots, 10$ is the empirical density function of quality in quadropoly. In the second step, these estimated α 's are used to estimate the altruism distribution K .

Given preferences and a symmetric equilibrium, our Bayesian game with independent values is identified by the equilibrium quality being monotone in altruism. The basic games and identification are the same

as in GPV, whose two-step estimator for bidders' valuation distribution in first-price auctions is consistent and achieves optimal convergence rate with a properly chosen bandwidth. These results depend on the assumption that the unknown valuation distribution is smooth. However, subjects in our game choose from only 11 possible qualities. We therefore can only estimate the unknown altruism distribution by histograms with 11 possible values. Even with more subjects, we would be unable to approximate a smooth distribution by histograms with a limited number of values.

4.3 Estimates of altruism distributions

We assume that the utility function U is linear: $U(x) = x$. In this case, α is the marginal rate of substitution between patient benefit bq and profit $p - cq^2$. Our main results will be based on this structural assumption. When U is linear, for monopoly we have

$$\alpha = \frac{2cq}{b}, \quad (16)$$

for duopoly, we have

$$\alpha = \frac{2cq \int_0^{10} S(q; x) dG(x) - (p - cq^2) \times \int_0^{10} bS(q; x)[1 - S(q; x)] dG(x)}{b \int_0^{10} S(q; x) dG(x) + bq \int_0^{10} bS(q; x)[1 - S(q; x)] dG(x)}. \quad (17)$$

For brevity, we do not write down the corresponding expression for α under quadropoly.

We have also used the alternate assumption of the utility function exhibiting a constant coefficient of absolute risk aversion.¹¹ The estimation results for $U(x) \equiv 1 - \exp(-rx)$ are in Appendix B. There we set the coefficient of absolute risk aversion r at 0.10. (We have also obtained results for r set at 0.05 and 0.15. Results turn out to be similar and are available from the authors.) The drawback is that the marginal rate of substitution between patient benefit and profit varies with the quality level, so the estimated value of α is not so easy to interpret.

We first present summary statistics of the estimated altruism distributions. Table 3 lists the means of the estimated α distributions in monopoly. We use these estimated monopoly means as normalization. In

¹¹CARA is a common functional form for risk preferences in the literature. See, for example, Barseghyan et al., 2018. It has been used for estimating risk preferences from individual-level data in contexts such as property insurance (Cohen and Einav, 2007; Barseghyan et al., 2016), game shows (Beetsma and Schotman, 2001; Andersen et al., 2008), and health insurance (Einav et al., 2013; Handel and Kolstad, 2015). In experiments, the CARA specification also has been used for estimating risk preferences (Harrison and Rutström, 2008).

Table 3: Estimated means of α in monopoly

Incentive configurations	mean
($p = 10, c = 0.075, b = 0.5$)	1.252
($p = 10, c = 0.075, b = 1$)	0.622
($p = 10, c = 0.1, b = 0.5$)	1.515
($p = 10, c = 0.1, b = 1$)	0.746
($p = 15, c = 0.075, b = 0.5$)	1.446
($p = 15, c = 0.075, b = 1$)	0.725
($p = 15, c = 0.1, b = 0.5$)	1.805
($p = 15, c = 0.1, b = 1$)	0.889

duopoly and quadropoly, for each incentive configuration, we subtract the estimated monopoly mean from each estimated α . This normalization uses the estimated monopoly mean as the origin. In Table 4, we present the normalized means and standard deviations of the 24 altruism distributions. Due to the normalization, each reported monopoly α distribution in Table 4 has a zero mean. Across a row in Table 4, for example, the magnitude -1.335 for the duopoly α mean in incentive configuration ($p = 10, c = 0.075, b = 0.5$) says that when the market changes from monopoly to duopoly, the average altruism parameter has decreased by 1.335 .

 Table 4: Normalized means and standard deviations of α distributions

Incentive configurations	Monopoly		Duopoly		Quadropoly	
	mean	st. dev.	mean	st. dev.	mean	st. dev.
($p = 10, c = 0.075, b = 0.5$)	0	0.898	-1.335	0.939	-1.579	0.766
($p = 10, c = 0.075, b = 1$)	0	0.448	-0.812	0.612	-0.985	0.657
($p = 10, c = 0.1, b = 0.5$)	0	1.117	-1.378	0.903	-2.233	1.710
($p = 10, c = 0.1, b = 1$)	0	0.559	-0.882	0.725	-1.069	0.822
($p = 15, c = 0.075, b = 0.5$)	0	1.028	-1.980	0.928	-2.382	0.980
($p = 15, c = 0.075, b = 1$)	0	0.512	-1.244	0.767	-1.471	1.138
($p = 15, c = 0.1, b = 0.5$)	0	1.308	-2.001	1.327	-2.428	1.147
($p = 15, c = 0.1, b = 1$)	0	0.638	-1.207	0.827	-1.485	1.016

The striking observation is that across each row, the average altruism has decreased from monopoly to duopoly, and then decreased further more from duopoly to quadropoly! This is clear evidence that competition reduces altruism on average. Standard deviations also tend to be different, but the pattern is not so uniform.

We now present the estimated α 's and their frequencies. Each of the α estimate is a nonlinear transformation of the chosen quality and the empirical quality distribution, and market and incentive-configuration parameters. The frequency for each α estimate is the same as the quality frequency, which are in Figures

1 to 3, so we do not write the frequencies again. We maintain the normalization by measuring α estimates from the means, which are in Table 3. In Table 5, we list the normalized estimated α 's corresponding to each quality between 0 and 10.

Table 5: Estimated monopoly α values, normalized at mean										
$q = 0$	$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$	$q = 8$	$q = 9$	$q = 10$
$(p = 10, c = 0.075, b = 0.5)$										
-1.252	-0.952	-0.652	-0.352	-0.052	0.248	0.548	0.848	1.148	1.448	1.748
$(p = 10, c = 0.075, b = 1)$										
-0.622	-0.472	-0.322	-0.172	-0.022	0.128	0.278	0.428	0.578	0.728	0.878
$(p = 10, c = 0.1, b = 0.5)$										
-1.515	-1.115	-0.715	-0.315	0.085	0.485	0.885	1.285	1.685	2.085	2.485
$(p = 10, c = 0.1, b = 1)$										
-0.746	-0.546	-0.346	-0.146	0.054	0.254	0.454	0.654	0.854	1.054	1.254
$(p = 15, c = 0.075, b = 0.5)$										
-1.446	-1.146	-0.846	-0.546	-0.246	0.054	0.354	0.654	0.954	1.254	1.554
$(p = 15, c = 0.075, b = 1)$										
-0.725	-0.575	-0.425	-0.275	-0.125	0.025	0.175	0.325	0.475	0.625	0.775
$(p = 15, c = 0.1, b = 0.5)$										
-1.805	-1.405	-1.005	-0.605	-0.205	0.195	0.595	0.995	1.395	1.795	2.195
$(p = 15, c = 0.1, b = 1)$										
-0.889	-0.689	-0.489	-0.289	-0.089	0.111	0.311	0.511	0.711	0.911	1.111

The frequencies of these normalized estimated α 's are in the following histograms in Figure 4. In these histograms, and later ones to be presented, we do not use identical scales on the horizontal axis. The 8 histograms exhibit various spreads. Due to the nonlinear transformation from the observed qualities to the estimated α , the actual values differ considerably across different incentive configurations. However, these histograms show that altruism distributions are diverse.

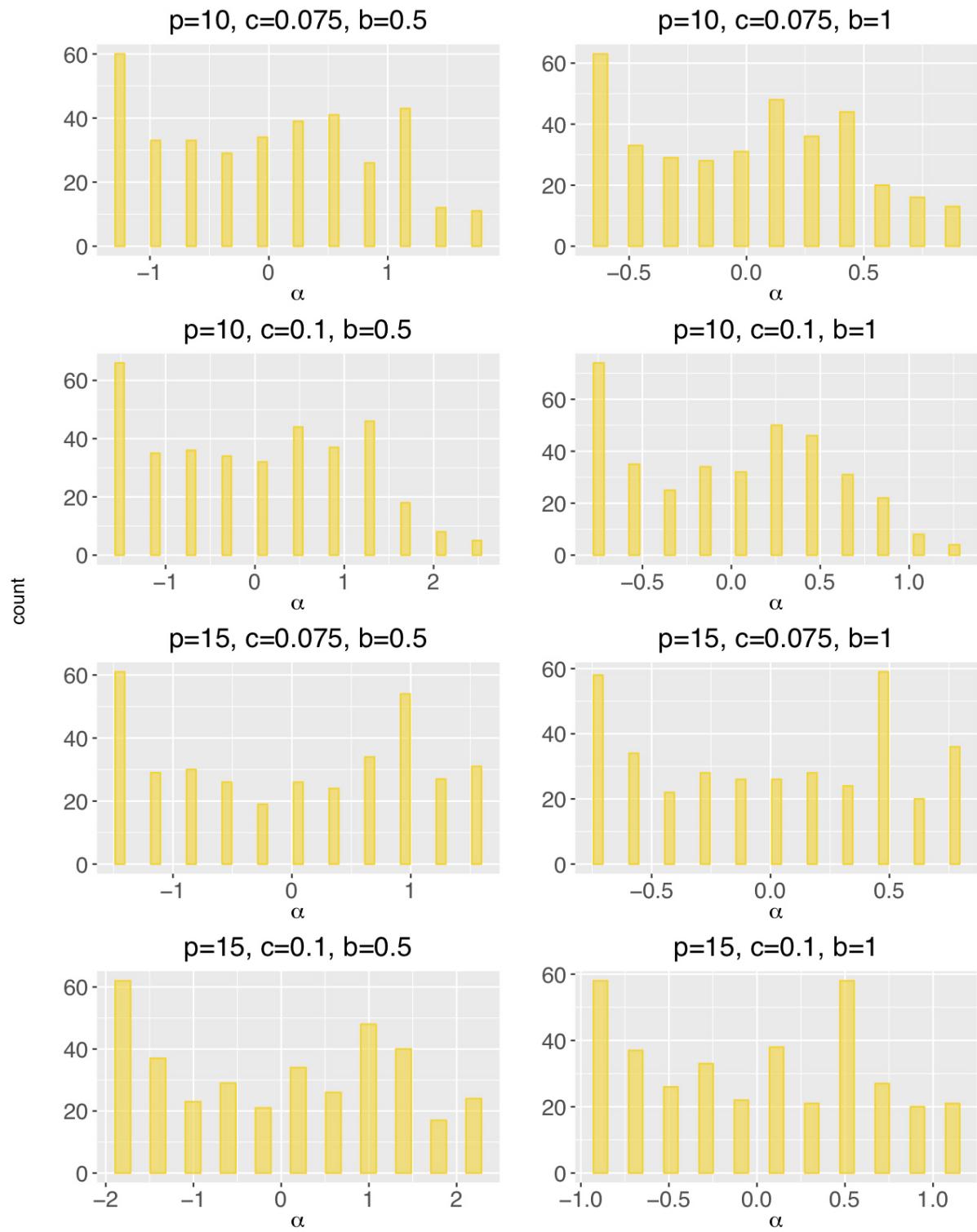


Figure 4: Histograms of estimated α in each incentive configuration in monopoly

Next, we turn to estimated duopoly α (again normalized by the corresponding monopoly mean) in Table 6; we do not report those α when the corresponding quality was chosen by none of the subjects. The corresponding histograms are in Figure 5. The frequency for each α estimate is the same as the corresponding quality frequency, which is in Figure 2.

Table 6: Estimated duopoly α values, normalized at monopoly mean

$q = 0$	$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$	$q = 8$	$q = 9$	$q = 10$
$(p = 10, c = 0.075, b = 0.5)$										
-10.486 - -5.422 -4.272 -3.430 -2.758 -2.186 -1.668 -1.177 -0.689 -0.187										
$(p = 10, c = 0.075, b = 1)$										
-8.148 - -3.359 -2.603 -2.079 -1.682 -1.359 -1.071 -0.792 -0.506 -0.187										
$(p = 10, c = 0.1, b = 0.5)$										
- -7.4 - -4.289 -3.364 -2.608 -1.942 -1.321 -0.710 -0.088 0.559										
$(p = 10, c = 0.1, b = 1)$										
-8.824 -4.912 - -2.613 -2.038 -1.607 -1.244 -0.900 -0.542 -0.141 0.332										
$(p = 15, c = 0.075, b = 0.5)$										
- - - -6.430 -5.252 -4.349 -3.613 -2.979 -2.403 -1.851 -1.296										
$(p = 15, c = 0.075, b = 1)$										
-11.376 -6.272 -4.496 -3.569 -2.923 -2.443 -2.079 -1.772 -1.489 -1.213 -0.900										
$(p = 15, c = 0.1, b = 0.5)$										
-15.714 - - - -6.486 -5.255 -4.284 -3.468 -2.744 -2.071 -1.412 -0.741										
$(p = 15, c = 0.1, b = 1)$										
-11.589 - - - -3.956 -3.156 -2.551 -2.082 -1.688 -1.326 -0.967 -0.568										

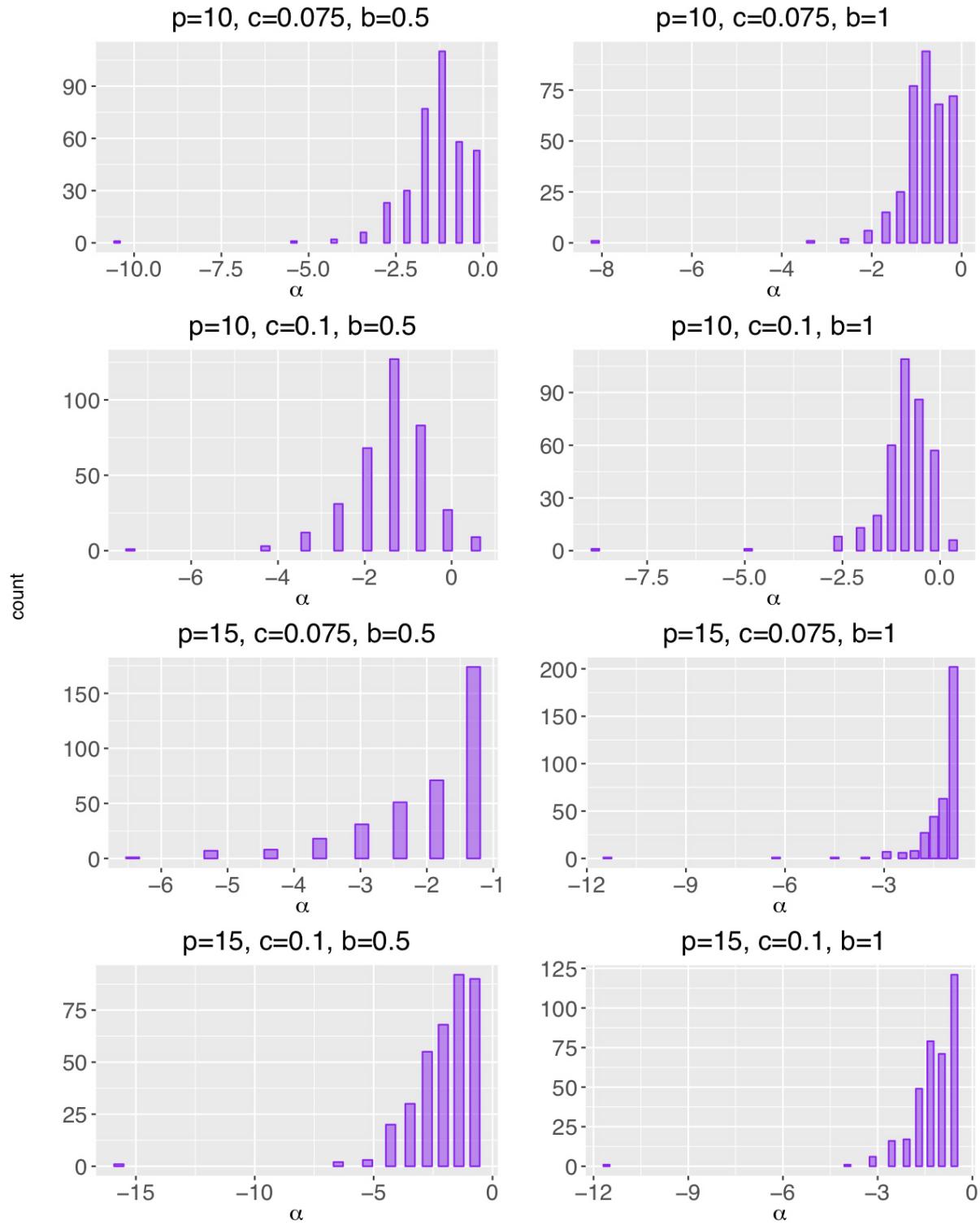


Figure 5: Histograms of estimated α in each incentive configuration in duopoly

The estimated values of α are very different from those in monopoly. The range has become much wider. From the histograms, we see that the higher values of estimated α 's have higher densities, but all of these higher values are below the corresponding monopoly mean. Subjects have become much less altruistic. Besides the stronger concentration, the α distributions appear to be strongly left-skewed in duopoly.

Table 7 presents the (normalized) α estimates for quadropoly, and Figure 6 presents the histogram. The frequency for each α estimate is the same as the corresponding quality frequency, which is in Figure 3. Similar to duopoly, quadropoly α distributions show a stronger concentration below the normalized monopoly mean and are left-skewed, as in duopoly.

Table 7: Estimated quadropoly α values, normalized at monopoly mean

$q = 0$	$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$	$q = 8$	$q = 9$	$q = 10$
$(p = 10, c = 0.075, b = 0.5)$										
-11.194	-	-	-	-3.733	-3.079	-2.540	-2.073	-1.648	-1.245	-0.845
$(p = 10, c = 0.075, b = 1)$										
-10.619	-	-3.753	-2.838	-2.258	-1.843	-1.521	-1.253	-1.015	-0.788	-0.550
$(p = 10, c = 0.1, b = 0.5)$										
-21.505	-11.209	-7.642	-	-4.539	-3.651	-2.941	-2.322	-1.730	-1.095	-0.331
$(p = 10, c = 0.1, b = 1)$										
-10.742	-	-	-2.866	-2.258	-1.815	-1.460	-1.154	-0.864	-0.560	-0.197
$(p = 15, c = 0.075, b = 0.5)$										
-16.391	-	-	-	-5.598	-4.707	-3.992	-3.390	-2.860	-2.374	-1.908
$(p = 15, c = 0.075, b = 1)$										
-15.717	-	-	-4.191	-3.362	-2.783	-2.346	-1.995	-1.698	-1.429	-1.163
$(p = 15, c = 0.1, b = 0.5)$										
-16.729	-	-	-6.908	-5.671	-4.721	-3.944	-3.277	-2.678	-2.117	-1.566
$(p = 15, c = 0.1, b = 1)$										
-15.883	-8.235	-5.619	-4.259	-3.403	-2.796	-2.329	-1.947	-1.614	-1.305	-0.987

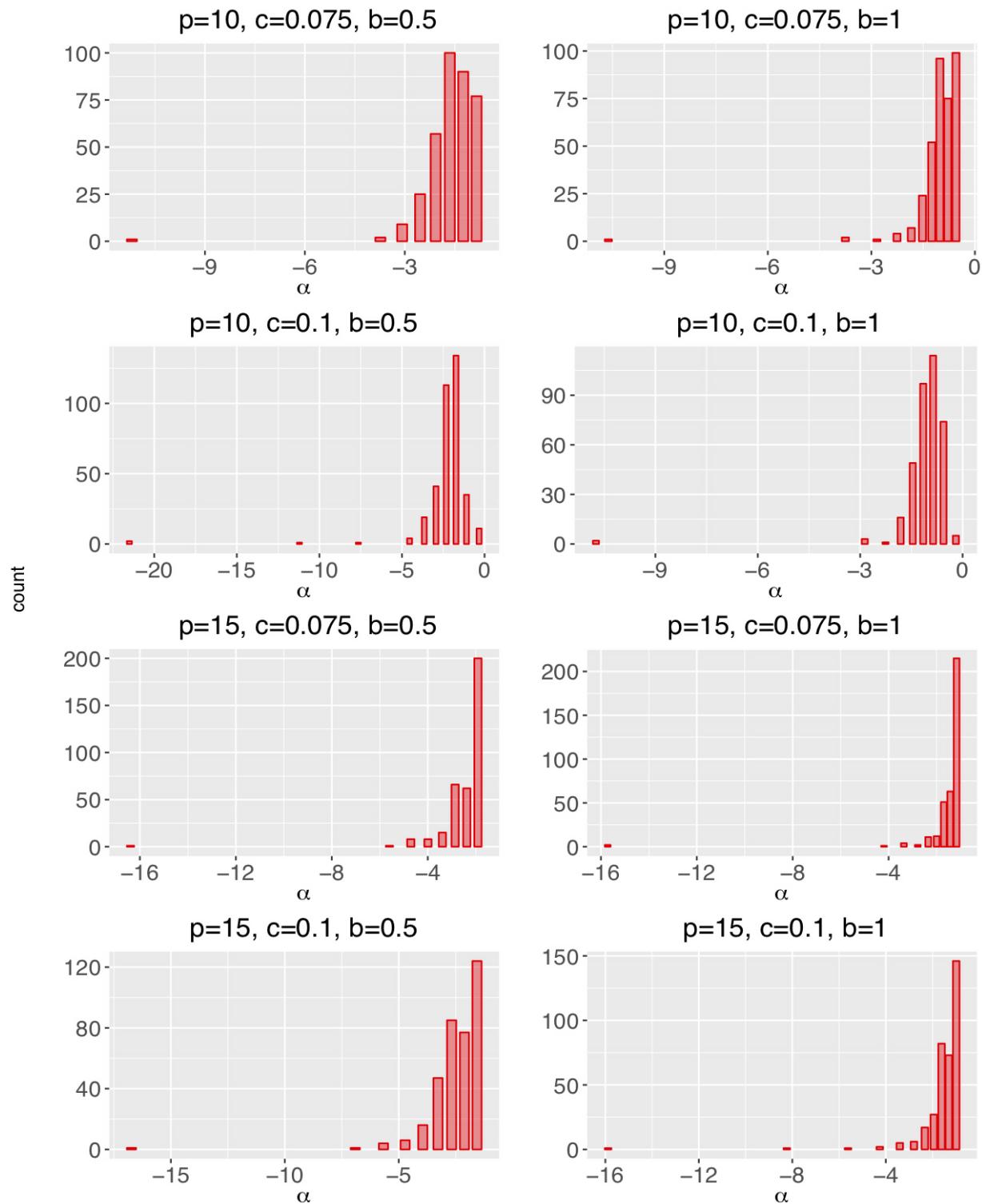


Figure 6: Histograms of estimated α in each incentive configuration in quadropoly

Estimations show striking differences between monopoly α distributions and the duopoly and quadropoly α distributions. Whereas preferences tend to exhibit diversity in monopoly, they are less diverse in duopoly, and becoming less so in quadropoly. Densities of estimated α 's tend to vary quite a lot in monopoly, but a lot less so in duopoly and quadropoly. Moreover, estimated α distributions tend to be left-skewed and being more concentrated at the high end of the distribution.

4.4 Statistical tests on altruism distributions

We can perform standard two-sample Kolmogorov-Smirnov (KS) tests on the (null) hypothesis that two estimated altruisms are drawn from the same continuous distribution.¹² The test statistic, KS distance, is the largest absolute difference between two empirical distribution functions; see, for example, Conover (1999). For two estimated α distributions, say \hat{F}_1 and \hat{F}_2 , their KS distance is defined by $KS_{1,2} \equiv \sup_a |\hat{F}_1(a) - \hat{F}_2(a)|$. We have plotted the 24 estimated α distributions in Figure 7. Note that these are plots of actual estimated α 's, not normalized at the mean of the monopoly α .

¹²Whereas the KS test is on drawn samples, our α 's are estimates. We did not manage to obtain the α 's sampling distributions, so our KS tests would not take sampling errors into account. However, as we show below, the rejections are very strong, so it is unlikely that KS tests performed poorly.

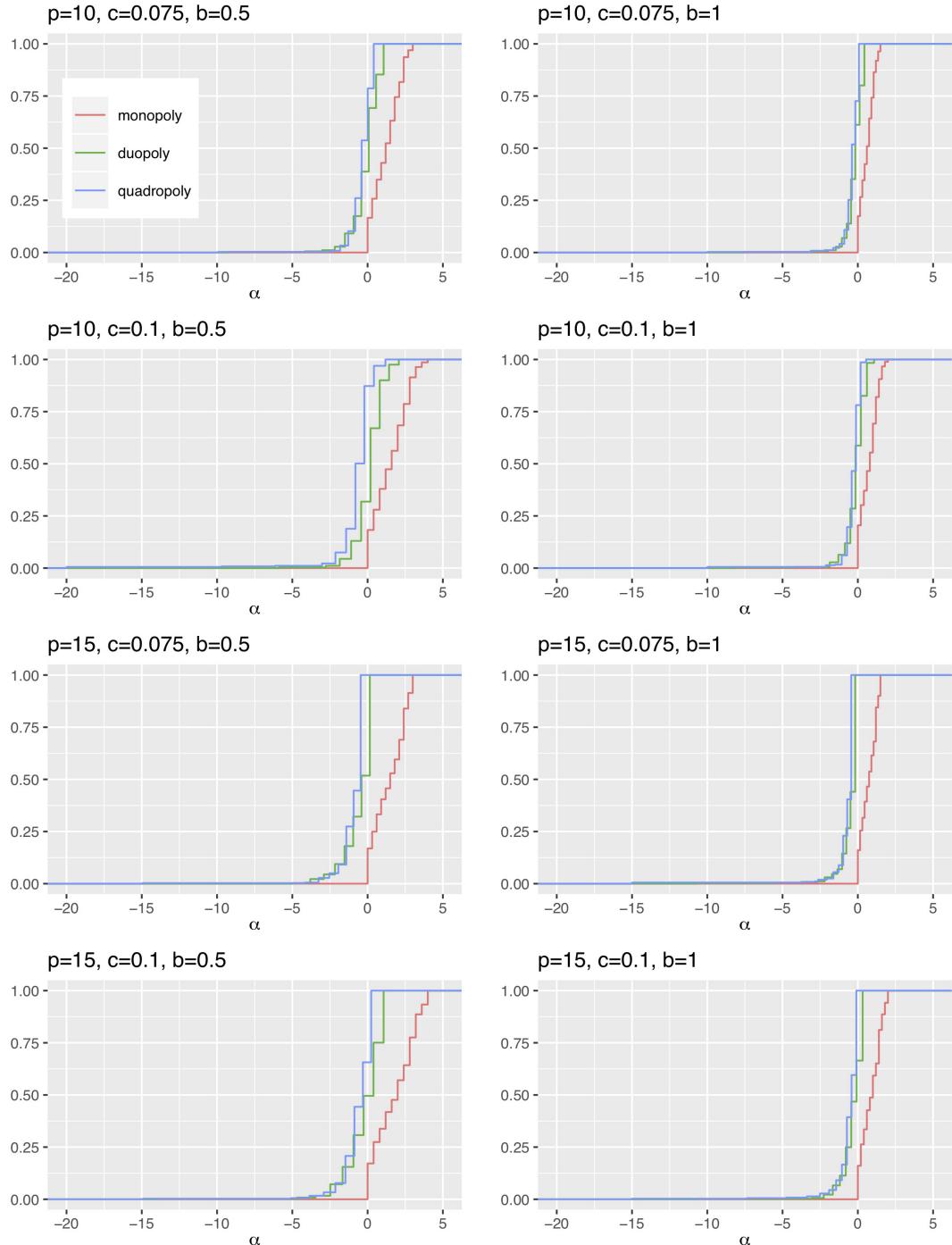


Figure 7: Distributions of estimated α in each market and in each incentive configuration.

In each of the 8 incentive configurations, we compare 3 α -distribution pairs: i) monopoly versus duopoly (M-D), ii) monopoly versus quadropoly (M-Q), and iii) duopoly versus quadropoly (D-Q). Table 8 presents the KS distances for all 24 pairs; all the p -values are very small (reported to be less than 2.2×10^{-16} by the software R , so omitted in the table). Except in one incentive configuration ($p = 10, c = 0.1, b = 0.5$), the KS distances are highest for M-Q, followed by M-D, and then D-Q. For incentive configuration ($p = 10, c = 0.1, b = 0.5$), the only difference is that D-Q distance is higher than M-D distance. The interpretation is that competition has an increasing effect on the reduction of altruism distribution. Because the p -values are so small, we reject the equality of the estimated α distributions in all comparisons.

Table 8: KS distances of α distributions between two markets for each incentive configuration

pair	KS distance	pair	KS distance
$p = 10, c = 0.1, b = 1$		$p = 10, c = 0.1, b = 0.5$	
M-D	0.587	M-D	0.521
M-Q	0.781	M-Q	0.873
D-Q	0.399	D-Q	0.554
$p = 10, c = 0.075, b = 1$		$p = 10, c = 0.075, b = 0.5$	
M-D	0.654	M-D	0.595
M-Q	0.825	M-Q	0.742
D-Q	0.388	D-Q	0.399
$p = 15, c = 0.1, b = 0.5$		$p = 15, c = 0.075, b = 1$	
M-D	0.662	M-D	1
M-Q	0.828	M-Q	1
D-Q	0.504	D-Q	0.559
$p = 15, c = 0.1, b = 1$		$p = 15, c = 0.075, b = 0.5$	
M-D	0.737	M-D	0.831
M-Q	1	M-Q	1
D-Q	0.532	D-Q	0.679

Next, for each of the 3 markets, we consider α distributions from the 8 different incentive configurations. There are 28 pairs for comparisons in each market. Table 9 presents the KS distances for these distributions. There, pairs are labeled by the order in which they were presented in Section 3.1, on page 14; for instance, the label 1-2 denotes the incentive-configuration pair ($p = 10, c = 0.1, b = 1$) and ($p = 10, c = 0.075, b = 1$). The KS distances vary across different pairs. All p -values are much smaller than 0.01 (and have been omitted in the table); we reject the hypothesis that any pair of the estimated α distributions are identical.

Table 9: KS distances of α distributions between two markets for each incentive configuration

pair	KS distances		
	Monopoly	Duopoly	Quadropoly
1-2	0.227	0.327	0.260
1-3	0.512	0.329	0.382
1-4	0.169	0.183	0.399
1-5	0.432	0.313	0.440
1-6	0.382	0.199	0.244
1-7	0.152	0.715	0.803
1-8	0.449	0.413	0.803
2-3	0.582	0.305	0.343
2-4	0.327	0.199	0.343
2-5	0.540	0.482	0.393
2-6	0.440	0.307	0.285
2-7	0.183	0.648	0.748
2-8	0.507	0.282	0.748
3-4	0.465	0.504	0.343
3-5	0.144	0.177	0.255
3-6	0.365	0.216	0.341
3-7	0.582	0.504	0.557
3-8	0.271	0.504	0.557
4-5	0.379	0.346	0.335
4-6	0.288	0.307	0.463
4-7	0.252	0.532	0.607
4-8	0.404	0.335	0.607
5-6	0.252	0.374	0.335
5-7	0.526	0.681	0.499
5-8	0.155	0.681	0.498
6-7	0.376	0.612	0.739
6-8	0.149	0.307	0.739
7-8	0.471	0.482	0.595

4.5 Counterfactual monopoly qualities from estimated duopoly and quadropoly altruism

Whereas Table 2 and Figures 1 to 3 report the outcomes, our structural estimation of α distributions in 4.2 can separately identify the effects (i) due to preferences change and (ii) due to market-incentive changes. However, results in Subsections 4.2 and 4.3 are obtained without explicit derivations of Bayes-Nash equilibria. One could not easily compute duopoly or quadropoly equilibrium quality distributions under the counterfactual that preference distributions remained unchanged at the monopoly configuration.

Instead, we perform counterfactual of the following sort. We use the estimated altruism distributions in an incentive configuration in duopoly or quadropoly to calculate the optimal qualities under monopoly. That is, we take α values and their frequencies from Tables 6 and 7 and feed them into the monopoly first-

order condition (4) to calculate optimal qualities. The next two figures show the counterfactual histograms of monopoly qualities when α 's are those identified in duopoly and quadropoly. In each counterfactual computation, the optimal qualities need not be integers, and we have limited the optimal qualities to be nonnegative. (Those estimated α in duopoly and quadropoly that are negative have been replaced by 0 to ensure a nonnegative optimal monopoly quality.)

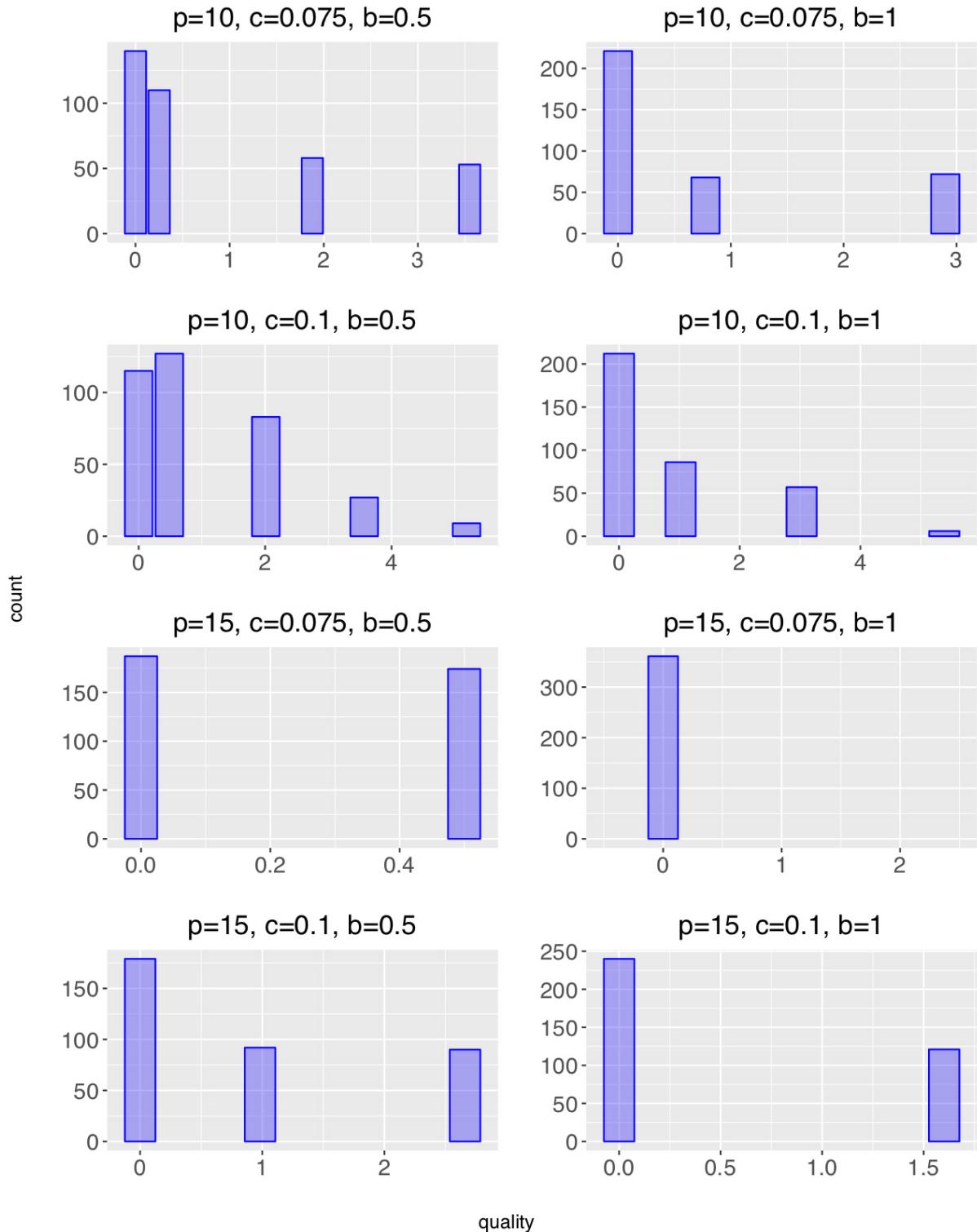


Figure 8: Counterfactual monopoly quality histogram from duopoly altruism α

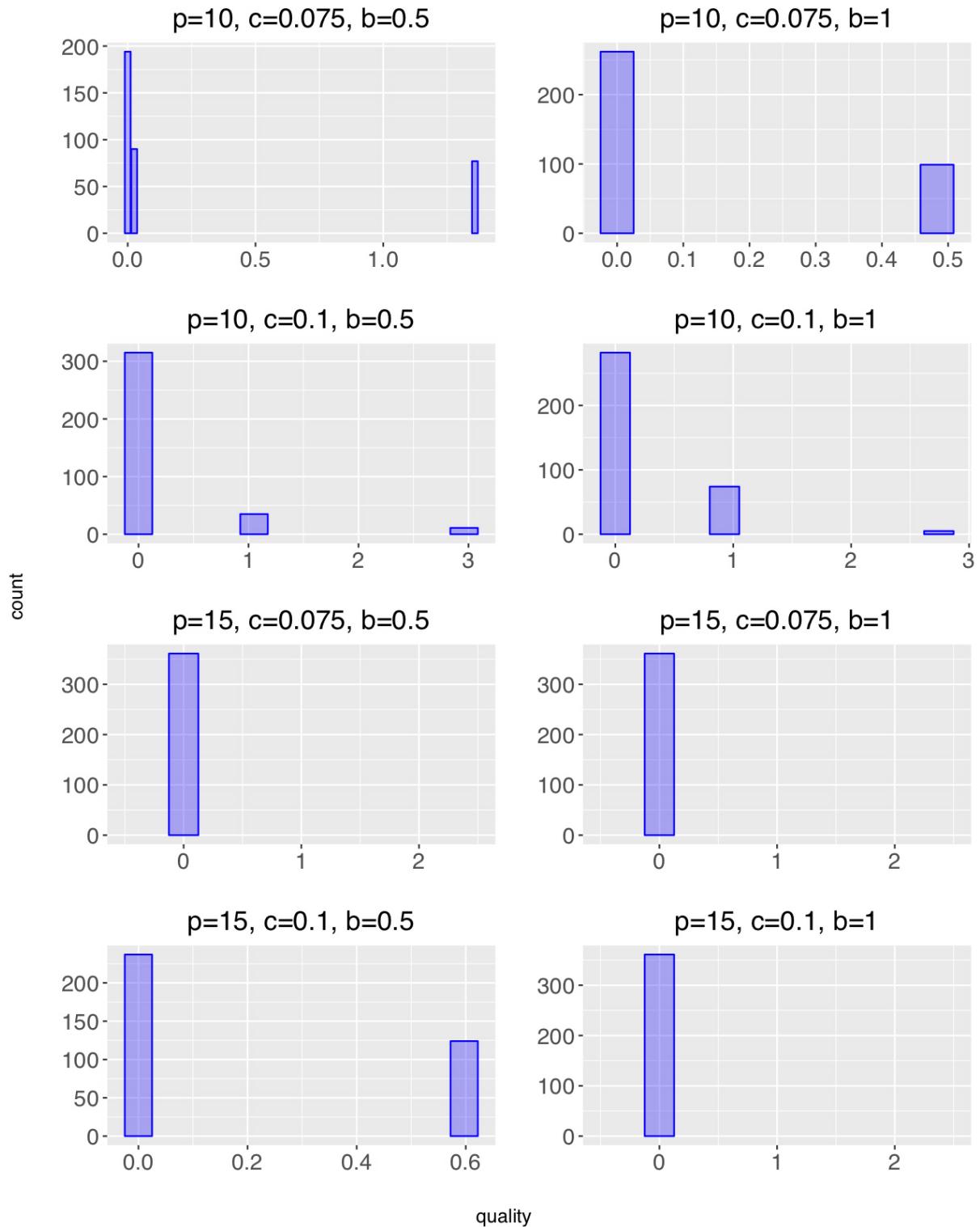


Figure 9: Counterfactual monopoly quality histogram from quadropoly altruism α

Differences between empirical monopoly qualities and counterfactual qualities are striking. Histograms in Figures 8 and 9 have no resemblance to those in the empirical quality distributions in Figure 1. This indeed indicates that markets and incentives do change preferences.

5 Reduced-form analysis of experimental data

We now present reduced-form analysis of subjects' quality choices. Table 2 already describes the 24 quality means and standard deviations for the 3 markets and 8 incentive configurations, and Figures 1 to 3 show the quality histograms. Here, we first present some aggregated descriptive statistics, and then regression results.

A subject makes 8 quality choices in each market. Of these 8, four of them are made with one fixed incentive-configuration parameter. For example, under monopoly at $p = 10$, a subject chooses 4 qualities, while cost and patient-benefit parameters vary between low and high. We record the average of these 4 qualities for each subject, and then we find the average of all 361 subjects (the average of a total of 1,444 quality choices). In Table 10, the first entry 3.959 records the mean of subjects' average quality choices at $p = 10$, and 2.900 is the corresponding standard deviation. Across that row, when the price is set at 15, the higher level, the mean becomes 4.652, and the standard deviation becomes 3.327. The relative difference, 0.175, equals $(4.652 - 3.959)/3.959$. The rest of Table 10 presents the quality-choice averages for each parameter in each market.¹³

From the first three rows with data entries in Table 10, average quality is higher in each market when the price is set at the higher level, but the relative difference declines as the market becomes more competitive. From the second set of data entries, average quality becomes lower when cost is set at the higher level, although the relative difference remains almost the same across markets. For patient benefits, quality averages exhibit a different pattern. For monopoly, a higher patient benefit results in a slightly lower average quality, whereas for duopoly and quadropoly, a high patient benefit results in slightly higher quality averages. But in all three markets, the relative difference seems very small.

¹³Table 10 aggregates the information in Table 2, which contains quality-choice means and standard deviations in each incentive-configuration-market constellation.

Table 10: Descriptives on the variations in price, costs, and patient benefit

Parameter	Low parameter level (N=1,444, per market)		High parameter level (N=1,444, per market)		Relative difference
	Mean	st. dev.	Mean	st. dev.	
Price ($p = 10; p = 15$)					
Monopoly	3.959	2.900	4.652	3.327	0.175
Duopoly	7.442	1.573	8.595	1.625	0.155
Quadropoly	7.841	1.479	8.862	1.484	0.130
Cost ($c = 0.075; c = 0.1$)					
Monopoly	4.493	3.227	4.118	3.038	-0.083
Duopoly	8.380	1.660	7.657	1.662	-0.086
Quadropoly	8.704	1.489	8.000	1.564	-0.081
Patient benefit ($b = 0.5; b = 1$)					
Monopoly	4.323	3.150	4.287	3.128	-0.008
Duopoly	7.925	1.668	8.112	1.726	0.024
Quadropoly	8.310	1.523	8.393	1.608	0.010

We next use ordinary least square regressions to study the effect of market competition and incentive-configurations:

$$q_i = \beta_0 + \beta_1 D + \beta_2 Q + \gamma_1 Price + \gamma_2 Cost + \gamma_3 Benefit + \psi \mathbf{X}_i + \varepsilon_i \quad (18)$$

where q_i , the dependent variable, is subject i 's quality choice, and β_0 is the intercept. Experimental manipulations are defined by a set of dummies. Regarding monopoly as the reference market, we use the dummy variables D and Q to represent duopoly and quadropoly, respectively; a dummy is set to 1 when the quality on the left-hand side has been chosen under the corresponding market condition. The *Price*, *Cost*, and *Benefit* variables are also dummies. The variable *Price* takes the value of 1 when price p is equal to the high level of 15; it takes the value at 0 otherwise. Similarly, *Cost* takes the value of 1 when $c = 0.1$, and *Benefit* takes the value of 1 when patient benefit $b = 1$; otherwise, they are 0. Equation (18) includes a vector of additional control \mathbf{X}_i of market orders (see Table 1) and session dummies, and finally ε_i is an error term. Model (1) in Table 11 presents the estimation results. In Model (2), we add market and incentive-configuration interaction terms.

From Table 11, quality is significantly higher in duopoly and quadropoly compared to monopoly, and the magnitudes are similar in both models. Wald tests indicate a highly significant difference between Duopoly

and Quadropoly ($p < 0.001$). For incentive configurations with a high price, a low cost, and a high patient benefits, qualities are significantly higher; see Model (1). With interaction terms in Model (2), the effects of price and cost remain qualitatively similar but the magnitudes have declined. The average benefit effect becomes insignificant; this suggests that the patient-benefit effect may be market specific. Using Wald tests, we find that market effects are significantly larger than market-configuration effects (at $p < 0.001$).

Table 11: Quality regressions

Model	(1)	(2)
Duopoly (D)	3.713*** (0.158)	3.545*** (0.157)
Quadropoly (Q)	4.046*** (0.157)	3.987*** (0.156)
High price (= 1 if $p = 15$)	0.955*** (0.029)	0.693*** (0.050)
High cost (= 1 if $c = 0.1$)	-0.601*** (0.024)	-0.375*** (0.046)
High benefit (= 1 if $b = 1$)	0.078*** (0.024)	-0.036 (0.043)
Duopoly \times High price		0.461*** (0.066)
Quadropoly \times High price		0.328*** (0.061)
Duopoly \times High cost		-0.348*** (0.056)
Quadropoly \times High cost		-0.328*** (0.055)
Duopoly \times High benefit		0.224*** (0.056)
Quadropoly \times High benefit		0.119** (0.055)
Market order and session dummies	Yes	Yes
Constant	3.971*** (0.400)	4.047*** (0.399)
Observations	8,664	8,664
Subjects	361	361
R^2	0.445	0.447

Notes: OLS; robust standard errors clustered for subjects in brackets; *** for $p < 0.01$; ** for $p < 0.05$

From Models (1) and (2) results, more intense market competition has implemented higher equilibrium

qualities. An interpretation of an unqualified success of competition (under regulated prices) on implementing higher qualities, however, is misguided. Bayes-Nash equilibrium qualities depend on preferences, markets, and incentive configurations. Our structural estimation supports reduction in altruism, which generally reduces subjects' qualities in equilibrium. The scenario is more appropriately described as a tug of war—between altruism reduction and competition-incentive disciplinary powers. In our setting, competition-incentive powers have won over altruism reduction.

6 Concluding remarks

Using behavioral data from an experiment in a health frame, we show that the altruistic preferences are affected by markets and incentives. We model subjects' preferences through a linear utility function whose marginal rate of substitution is interpreted as the degree of altruism. Subjects play a simultaneous-move incomplete information game when they compete with each other. Using the experimental data, we estimate the altruism distribution in each market-incentive environment. The estimation results show that subjects are less altruistic when they have to compete against each other.

Although our conclusion is that altruism has changed, we have maintained certain assumptions, both in the theoretical model and in the experiment. The structural model does require some consistency in preferences between different markets and incentive configurations. So to speak, we can estimate changing preferences only if those changes are not so drastic. We narrow down our study to one altruism parameter.

The assumption that individuals are interested only in profits and patient benefits is maintained throughout. We would not be in a position to test if subjects would become spiteful, winning oriented, or fair-minded when they participate in duopoly or quadropoly. Our design does minimize these contaminations, however. We have only told subjects very sparse outcome information. Subjects never have learned that they have been “disadvantaged” by the rival, that their qualities have been higher or lower than rivals', or that their choices turn out to be similar or very different from the population averages. We have limited subjects' ability to learn about each other by implementing a simultaneous-move game. Interaction between subjects and learning about the population are both impossible in our design. Every attempt has been made to

ensure that a subject is playing against another randomly drawn subject, and only once.

We make the point that economic institutions may affect preferences in nontrivial ways. Economic institutions may shape preferences just as climate, cultural-historical events, physiology, and genetics.

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