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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 with 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 by trading off between profits and altruistic patient benefits. In duopoly and quadropoly, subjects play a simultaneous-move game. Uncertain about an opponent's altruism, each subject 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. Competition tends to reduce altruism, but duopoly and quadropoly equilibrium qualities are much higher than monopoly. Although markets crowd out altruism, the disciplinary powers of market competition are stronger. Counterfactuals confirm markets change preferences.

1. Introduction

Recent economic research has questioned whether high-powered incentives must result in more outputs or worker efforts. Besides financial reward and effort disutility, fairness, altruism and spite may also shape economic agents' behavior. These broad perspectives are particularly important in the health market. Provider altruism and professionalism have been shown to be critical in understanding markets and incentives, in theoretical models, empirical and field works, as well as experiments.

The usual research methodology says that given multi-dimensional preferences, economists can write analytical and empirical models to study markets and incentives. No matter how social preferences are determined, if they remain exogenous, the usual methodology remains valid. In this paper, we assess whether social preferences can be changed by markets and incentives; in other words, we assess if preferences differ across contexts and domains.[1] Our focus is on altruism, market competition, and incentives in health care. We present experimental evidence that altruistic preferences can be diminished by competition and altered by incentives. The usual research methodology may be invalid.

Our research proceeds in three steps. First, in the key conceptual starting point, we use a structural model to decompose behavioral changes into preference effects and market-incentive effects. We explicitly allow altruistic preferences to change according to markets and incentives. Behavioral changes are then results of markets and incentives changing preferences as well as equilibria.

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[1] See, for example, Barseghyan et al. (2011) and Einav et al. (2012).

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Second, we use a laboratory experiment in which incentives and market competition are exogenously varied. Such an environment offers a better chance for us to identify preferences than real data. The experimental framing is health care provision. Subjects are primed in a decision situation for other-regarding concerns. They choose health care qualities which affect their own payoffs and which benefit patients through a transfer to a charity for actual ophthalmic treatments. We also have taken care to insulate subjects, so such confounding factors as fairness, collusion, and spitefulness were 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 heterogeneous (which could be identified by a between-subject design).

Third, we adapt the nonparametric econometric method by Guerre et al. (2000) to estimate preference distributions. We estimate subjects' altruism distributions separately as subjects experience different market-incentive configurations. The nonparametric method does not restrict us to prespecified distribution classes.

We show that subjects become less altruistic when they have to compete against others in a duopoly or 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. Structural preference parameters vary according to competition and incentives. Equilibrium outcomes depend on both policy and preference changes.

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 depends 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 three markets, we vary 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 plays 24 games.

Each basic game is modeled as one of incomplete information. A player's altruism is his own private information, so each player is uncertain about other players' altruism. Uncertainty is described by a distribution, which, through subjects' play of a Bayes-Nash equilibrium, results in actual qualities. Inverting the Bayes-Nash equilibrium strategy, we estimate the altruism distribution, one for each of the 24 games.

Nonparametric estimations 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, 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 against crowding out. We reject the simplistic conclusion. Quality changes result from two effects: preference changes and market-incentive changes. The effects go in opposite directions. Market competitions reduce altruism, but also incentivize subjects. Market-incentive effect is stronger than preference-change effect in the experiment. The structural approach permits some counterfactual 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 brain electrochemical activities. We are neither in a position to render an opinion nor did we manage to use brain scans to detect 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. Perhaps competition has emphasized strategic plays more than altruistic concern towards patients.

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, and a discussion of our method. Section 5 presents the reduced-form analysis. The last section draws some conclusion.

We provide an extensive Online Appendix. There are three sections. Section A contains additional theoretical considerations; we present a set of preferences about what we call Extended Concern (A.1), and the difficulties with asymmetric Bayes-Nash equilibria (A.2). Section B presents experiment materials (Instructions in B.1; control questions in B.2; and screen shots and experiment parameters in B.3). Section C collects some altruism parameter estimates and robustness checks: C.1 contains altruism and distribution distance estimates; C.2 presents an alternate utility function and the between-subject subsample; C.3 allows for subjects' quality choices being corner solutions; C.4 varies the coefficient of absolute risk aversion.

1.1. Literature review

We contribute to recent literature on markets' effects on prosocial-moral behavior. Falk and Szech (2013) show that bilateral and multilateral market interactions reduce morals compared to individual decisions; they attribute this to subjects willing to accept a negative market externality. Bartling et al. (2015, 2019) report less socially responsible behavior in posted-price markets compared to non-market contexts. For markets with negative externalities, Kirchler et al. (2016) analyze how characteristics in double auctions influence moral behavior and Sutter et al. (2020) report that moral costs decrease trading volume.

Some recent experimental evidence disputes the above findings. Bartling et al. (2023) report that repeated play rather than market interaction causes moral erosions.[2] This is also supported by recent theoretical work on markets and social preferences. Dufwenberg et al. (2011) show that individuals with other-regarding preferences behave like selfish individuals in a Walrasian equilibrium with given prices. Dewatripont and Tirole (2022) focus on how market interactions affect individuals' tradeoffs between profits and moral concerns. Whereas market interactions, in their setup, do not change preferences, competition can erode equilibrium ethics when suppliers have heterogeneous concerns.

Preferences are typically inferred from observed behaviors in the experimental market games. This method is natural in single-person decisions. However, we consider multi-person strategic interactions. Equilibrium outcomes depend on preferences and market. Our contribution is a method to decompose behavioral changes into those due to preference and market changes. Our approach is probably quite close to Bartling et al. (2015), who structurally estimate consumers' preferences. Whereas they find that the average buyer cares for a third-party's earnings, preference estimates remain unchanged in different market treatments. In their setup, however, consumers and firms do not engage in a strategic game.

Besides potential market effect, economic incentives are often found to reduce prosocial behavior (e.g., Bowles and Polania-Reyes (2012)). Some experimental evidence tends to confirm crowding out (e.g., Gneezy and Rustichini (2000), Falk and Kosfeld (2006) and Mellström and Johannesson (2008)). Our paper, however, goes beyond identifying crowding out only in terms of outcomes. Incentive schemes are disciplinary, even when they may erode social motives. Incentives and social motives pull in different directions, and it is an empirical matter which is stronger.

With our structural estimation-approach, we relate to studies measuring social preferences such as inequality aversion and reciprocity (e.g., Charness and Rabin (2002) and Bellemare et al. (2008)), and altruism from experiments (e.g., Andreoni (1989), Andreoni and Miller (2002) and Fisman et al. (2007)).[3] A few studies use *parametric* structural estimation approaches to measure altruism from experiments in health contexts or with medical students and physicians (Godager and Wiesen, 2013; Wang et al., 2020; Li et al., 2017, 2022; Li, 2018; Attema et al., 2023). These studies report heterogeneity in altruism, none accounts, however, for the influence of competition.

Finally, our (reduced form) analysis relates to the health economics literature on competition and quality. Brekke et al. (2011) show that, with semi-altruistic providers, competition may have ambiguous effects on hospital quality. In an experimental study backed by theory, Brosig-Koch et al. (2017a) report that the market effect depends on individuals' concern for patients' health benefits. Some empirical studies seem to support the positive effect of competition on quality (e.g., Gravelle et al. (2019) and Dietrichson et al. (2020)). Scott et al. (2022), however, find mixed effects of competition and rather emphasize the importance of differences in demand, costs, and profit. These findings resonate with our reduced form analyses. Keeping patient demand constant, we find that higher prices increase quality and higher costs reduce quality.

2. A model of altruism and competition

Subjects in the experiment role play providing medical services at some quality to patients.[4] The three markets are monopoly, duopoly, and quadropoly. The monopoly game is a single-person decision problem, and the simultaneous-move duopoly and quadropoly games are strategic problems.

Physician providing costly care quality is likened to physician exerting costly efforts. In the course of a treatment, a physician has to plan, execute, and follow-up with patient care. In our experimental design, qualities may refer to physician effort. However, qualities or efforts are not directly paid for because they are non-contractible. Quality provision is driven entirely by altruism in monopoly, and, additionally, by competition in duopoly and quadropoly.

2.1. Quality choices and preferences

A subject receives a fixed payment $p > 0$ for each patient that he or she treats. A subject's quality choice is a continuous variable between 0 and 10. 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, where $b > 0$ is the benefit parameter. We call the environment defined by the three parameters, payment p, cost c, and benefit b, an *incentive configuration*.

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[2] For further discussion of Falk and Szech's (2013) results, see Breyer and Weimann (2015).

[3] For an excellent summary, see DellaVigna (2018). Using data from field experiments, a few papers structurally infer social preferences to identify differences between charitable giving and worker effort; see DellaVigna et al. (2012) and DellaVigna et al. (2022).

[4] There 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 Section 3.1.

Given the altruistic framing, we let a subject's preferences be $\alpha bq + U(p - cq^2)$, 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 the subject's own profit $U(p - cq^2)$. Framing and priming affect subjects differently; accordingly, the preference weight on patient benefit, α, is a random variable on an interval $[\underline{\alpha}, \overline{\alpha}] \subset \mathbb{R}$ with some distribution.

2.2. Demand

There are 100 patients who are to receive medical services. Under monopoly, each subject makes a quality decision, q between 0 and 10, for all patients. In duopoly and quadropoly, subjects choose qualities simultaneously. Subjects' quality profile determines subjects' logistic demands. Let q_1 and q_2 be qualities chosen by subject 1 and subject 2 in a duopoly. The numbers of patients for subjects 1 and 2 are, respectively,

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

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

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

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 noises according to type I extreme-value distribution.

2.3. Monopoly, duopoly and quadropoly

In monopoly, a 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, $q = 10$. Generally, a subject's optimal quality is given by the first-order condition:

$$\alpha b - U'(p - cq^2) \times 2cq = 0, \tag{3}$$

which defines a monotone relationship between α and the optimal quality:

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

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

Subjects also play the duopoly and quadropoly games; we lay out details in duopoly, but 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.

Duopoly is modeled as a Bayesian game. We let each subject' altruism parameter, α, be drawn independently from a random variable with distribution F and density f on support $[\underline{\alpha}, \overline{\alpha}]$. 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.

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

$$\begin{aligned}\mathrm{EU}(q_1; q') &= \int_{\underline{\alpha}}^{\overline{\alpha}} \left\{ [\alpha_1 bq_1 + U(p - cq_1^2)] \left[\frac{100\exp(bq_1)}{\exp(bq_1)+\exp(bq'(x))} \right] \right\} \mathrm{d}F(x) \\ &= [\alpha_1 bq_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q_1; q'(x)) \mathrm{d}F(x),\end{aligned} \tag{5}$$

where $S(q_1; q') \equiv \dfrac{\exp(bq_1)}{\exp(bq_1)+\exp(bq')}$ denotes the market share, which is uncertain due to the rival subject's stochastic altruism and hence his quality choice. A subject choosing a higher quality earns a higher market share:

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

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. The expression in (5) only concerns those patients the subject serves. Remark 3 at this end of this subsection discusses this specification, and Section A.1 in the Online Appendix provides mathematical details.

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

$$q(\alpha_1; q') = \underset{q_1}{\operatorname{argmax}}[\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q_1; q'(x)) \mathrm{d}F(x) \tag{6}$$

be subject 1's best response against the rival's strategy $q'(\alpha) : [\underline{\alpha}, \overline{\alpha}] \to [0, 10]$. 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. We discuss asymmetric Bayes-Nash equilibria in Section 4.6.

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

$$q^*(\alpha) = \underset{q}{\operatorname{argmax}}\ [\alpha b q + U(p - cq^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q; q^*(x)) \mathrm{d}F(x). \tag{7}$$

The usual characterization of an equilibrium is by means of the first-order condition for the maximization of (5) or the best response in (6). Given a rival's strategy q', for the maximization of expected utility in (5), we obtain the first-order derivative with respect to q_1:

$$\begin{aligned} \frac{\partial\, \mathrm{EU}(q_1; q')}{\partial q_1} &= [\alpha_1 b - 2cq_1 U'(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q_1; q'(x)) \mathrm{d}F(x) \\ &+ [\alpha_1 b q_1 + U(p - cq_1^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 b S(q_1; q'(x))[1 - S(q_1; q'(x))] \mathrm{d}F(x). \end{aligned} \tag{8}$$

By setting the first-order derivative to zero, we obtain the implicit function that defines the best response at α.

At the symmetric Bayes-Nash equilibrium, $q^* : [\underline{\alpha}, \overline{\alpha}] \to [0, 10]$, each subject has the same first-order condition, so it is given by setting (8) to 0 at each $\alpha \in [\underline{\alpha}, \overline{\alpha}]$ with q' set to q^*:

$$\begin{aligned} &[\alpha b - 2cq^*(\alpha) U'(p - cq^*(\alpha)^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q^*(\alpha); q^*(x)) \mathrm{d}F(x) \\ &+ [\alpha b q^*(\alpha) + U(p - cq^*(\alpha)^2)] \times \int_{\underline{\alpha}}^{\overline{\alpha}} 100 b S(q^*(\alpha); q^*(x))[1 - S(q^*(\alpha); q^*(x))] \mathrm{d}F(x) = 0. \end{aligned} \tag{9}$$

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* $q^* : [\underline{\alpha}, \overline{\alpha}] \to [0, 10]$ *is monotone increasing in* α.

Proof of Lemma 1. Using the first-order derivative of EU with respect to q_1 in (8), we further differentiate this with respect to α_1 to obtain

$$\frac{\partial^2\, \mathrm{EU}(q_1; q')}{\partial \alpha_1 \partial q_1} = b \int_{\underline{\alpha}}^{\overline{\alpha}} 100 S(q_1; q'(x)) \mathrm{d}F(x) + b q_1 \int_{\underline{\alpha}}^{\overline{\alpha}} 100 b S(q_1; q'(x))[1 - S(q_1; q'(x))] \mathrm{d}F(x) > 0.$$

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. The following describes how we will use the equilibrium play data.

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 $G^* : [0, 10] \to [0, 1]$, we conclude that for $\widetilde{q} \in [0, 10]$, $G^*(\widetilde{q}) = F(\widetilde{\alpha})$, where $q^*(\widetilde{\alpha}) = \widetilde{q}$.

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 Section 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 no 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, her market share now is $S(q_i; q_{-i}) = \dfrac{\exp(bq_i)}{\sum_{j=1}^4 \exp(bq_j)}$, where we use q_{-i} to denote the quality vector

(q_1, q_2, q_3, q_4) with the ith element omitted. Given strategies q_j, $j = 1, 2, 3, 4$, $j \neq i$, if subject i chooses quality q_i at α_i, the expected utility is

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

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 $\alpha \in [\underline{\alpha}, \overline{\alpha}]$,

$$q^{**}(\alpha) = \underset{q}{\operatorname{argmax}} \ \left[\alpha b q + U(p - c q^2)\right] \int\int\int \left\{100 S(q; q_{-i}^{**}(\alpha_{-i}))\right\} \prod_{j=1,\ j\neq i}^{4} \mathrm{d}K(\alpha_j). \quad (10)$$

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* $q^{**} : [\underline{\alpha}, \overline{\alpha}] \to [0, 10]$ *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 $L^{**} : [0, 10] \to [0, 1]$.

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.

Remark 3 (*Extended Concern*)**.** We would like to comment on the altruistic expected utility specification in (5). An alternate view could be that a subject might enjoy some utility even if a patient was treated by a rival subject. If a rival offers q', the subject's expected utility from offering quality q_1 is now written as $S(q_1; q')[\alpha b q_1 + U(p - c q_1^2)] + [1 - S(q_1; q')]\beta b q'$, where β is a parameter for valuing patient's benefit from the rival's quality. This "extended concern" perspective (the β valuation of rival quality) has not been used before as far as we know. Prior research on altruistic providers in Brekke et al. (2011) and Brosig-Koch et al. (2017a), for example, use altruistic preferences similar to ours in (5). Perhaps, the reason is this. When subjects compete, an extended concern actually may reduce quality incentives because a subject tends to free-ride on the rival's quality. This amounts to an unnatural perspective: altruism and free-riding coexist. We provide the details in Section A.1 of the Online Appendix.

3. The experiment

3.1. Design

The experimental design implements the theoretical model. Role playing as physicians, subjects decide on the quality of health care for hypothetical patients.[5] Each subject chooses a medical-service quality q from a set $\{0, 1, 2, \ldots, 10\}$, rather than the continuous interval $[0, 10]$ as in the theoretical model. Three parameters determine payoffs: price to the physician p, cost parameter c, and patient benefit parameter, b. Profit is $p - cq^2$, and the patient benefit is bq.

We use a $2 \times 2 \times 2$ factorial design to vary each of the p, c, and b parameters. 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, and the benefit parameter b can be either 0.5 or 1. The full set of parameters are in Table B.1 in Section B.3 of the Online Appendix. A profile of price-cost-benefit parameters is called an incentive configuration; the $2 \times 2 \times 2$ variations set up 8 incentive configurations. There are 3 markets: monopoly, duopoly, and quadropoly. Each subject plays 24 games in the experiment: 8 incentive configurations by 3 markets. All monetary amounts were in terms of the experimental currency, Taler, which was later converted to Euro at the rate of 100:1.

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.[6]

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, ($p = 15$, $c = 0.075$, $b = 0.5$).

[5] Hypothetical patient profiles, characterizing patients through different benefits from medical treatment decisions, have been used in several behavioral experiments in health with medical and non-medical students (e.g., Hennig-Schmidt et al. (2011), Kesternich et al. (2015), Brosig-Koch et al. (2017a,b, 2023), Wang et al. (2020) and Waibel and Wiesen (2021)) and practicing physicians (e.g., Brosig-Koch et al. (2016, 2023)).

[6] It 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. Random rematching for 16 times for each subject also would be time consuming.

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

The common "random-choice" payment method is used 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; this avoids income effects and possibly keeps subjects' focus.

Subjects play a normal form game against others randomly drawn from a population. 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.

Our design rules out repeated plays, learning, and reputation. This is a design tradeoff. On the one hand, as our focus is on altruism, we 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; we have some discussion in Section 4.6. We focus on altruism, so it is inappropriate to introduce a control with patient benefits removed, or to make the benefits independent of subjects' quality choices.[7]

We do want to find out if subjects' preferences change according to markets and incentive configurations, hence our within-subject design. 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. The between-subject subsample serves as a comparison with the main within-subject design. The analysis is in Sections C.2.2 and C.2.3 of the Online Appendix. The results are consistent with the complete sample.

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 took place in October 2017 and in April 2018, at the Cologne Laboratory for Experimental Research of the University of Cologne, Germany. Almost all subjects were students from the University of Cologne. Participants were invited via the ORSEE platform (Greiner, 2015). In total, 361 subjects participated in the experiment.[8] Subjects on average were about 24 years old, with 55% being 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.[9]

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 (monopoly, duopoly, or quadropoly). Detailed instructions of each part would only be given at the start of that part. Participants had adequate time to read the instructions. The instructions can be found in Section B.1 of the Online Appendix. 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

[7] To 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 construed as any control or variant. Besides, we would not be able to control what subjects would think about what qualities were doing.

[8] We 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.

[9] We did not recruit medical students only; there were not enough such potential subjects. Some experimental studies indicated differences between medical and non-medical students' responses to financial incentives. Hennig-Schmidt and Wiesen (2014), Brosig-Koch et al. (2016, 2017b)), and Reif et al. (2020) show that students with non-medical majors respond somewhat stronger to financial incentives than medical students. However, effects are similar across subject pools. Further, experimental studies in non-market settings reported that medical students are more altruistic than non-medical students or those from a representative US sample (American Life Panel) with comparable ages (Li et al., 2017, 2022; Attema et al., 2023). However, for the 22 medical students in our sample, we observed very similar patterns in quality choices compared to others; they also raise qualities when the market becomes more competitive.

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

benefit parameters, and how quality choices might affect demands. Each subject must answer all control questions correctly before the start of each part. The control questions can be found in Section B.2 of the Online Appendix.

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 $\{0, 1, 2..., 10\}$. 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 Section B.3 of the Online Appendix. 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.

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 assistant then deposited the envelope in a nearby 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 any compassion motives. A similar procedure for making patient benefits meaningful to subjects has been applied by, for example, Hennig-Schmidt et al. (2011), Kesternich et al. (2015), and Brosig-Koch et al. (2017a,b).

Sessions lasted, on average, for about 90 min, 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, €2923.60 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 on average 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. Within a market, quality variations between the 8 incentive-configuration games seem quite modest.

For each of the 24 games, we draw the quality histograms; they are in Figs. 1 to 3, and the actual frequency of each quality between 0 and 10 is written at the top of each vertical bar. The 24 histograms show higher qualities in duopoly and quadropoly than monopoly, but the differences between duopoly and quadropoly appear to be slight. Quality frequencies are needed for the estimation of altruism parameters.

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

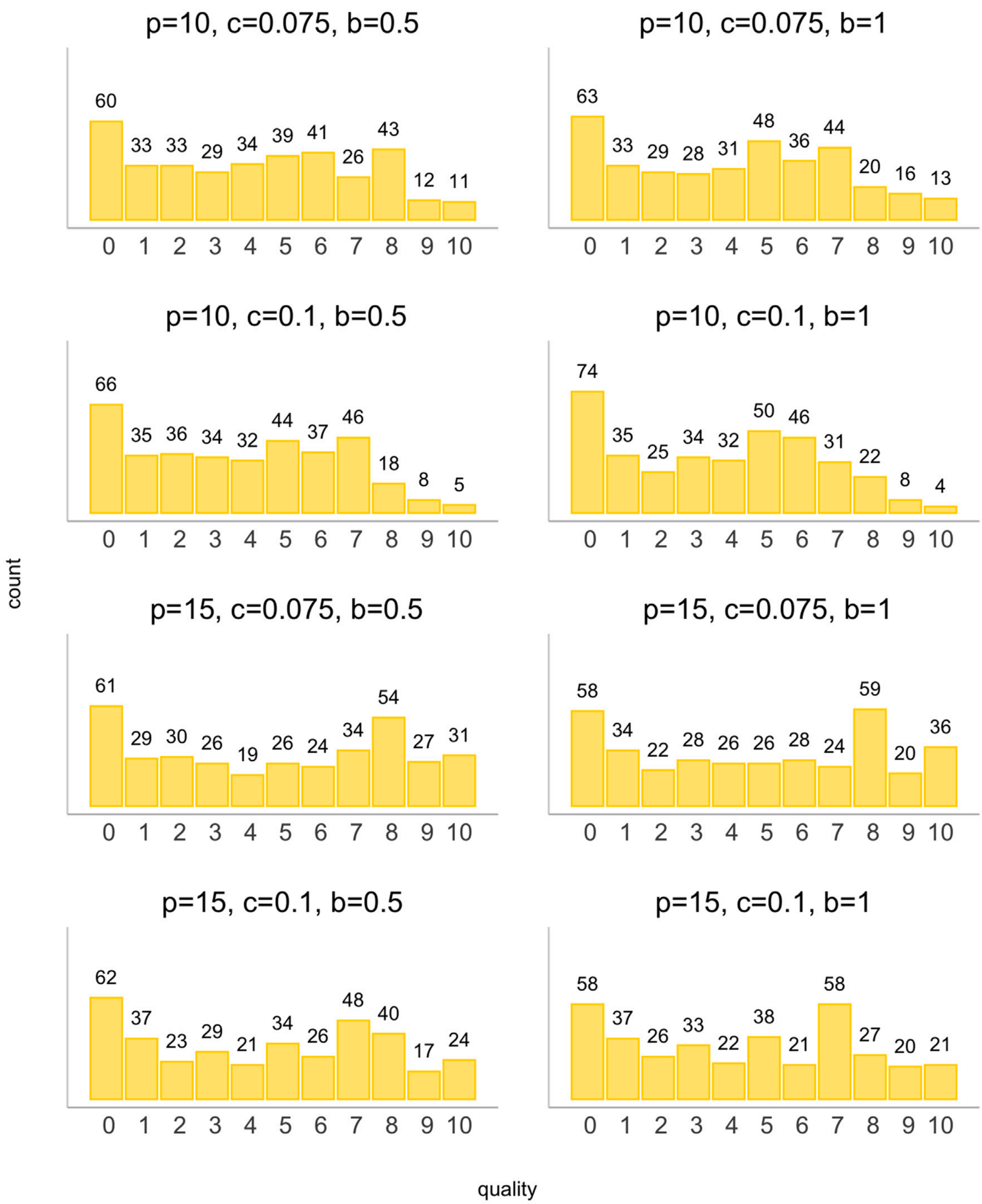

Fig. 1. Quality histograms in monopoly.

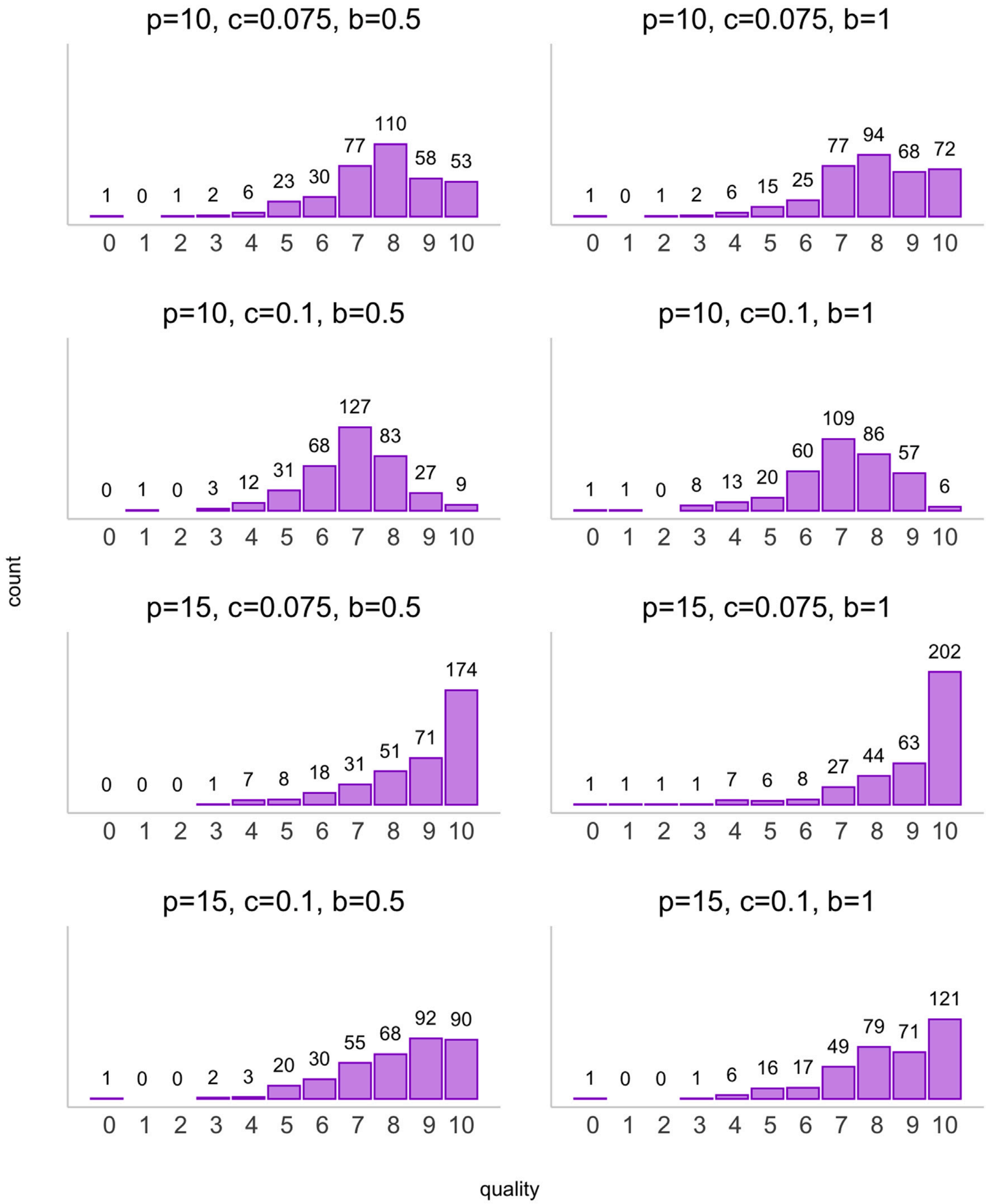

Fig. 2. Quality histograms in duopoly.

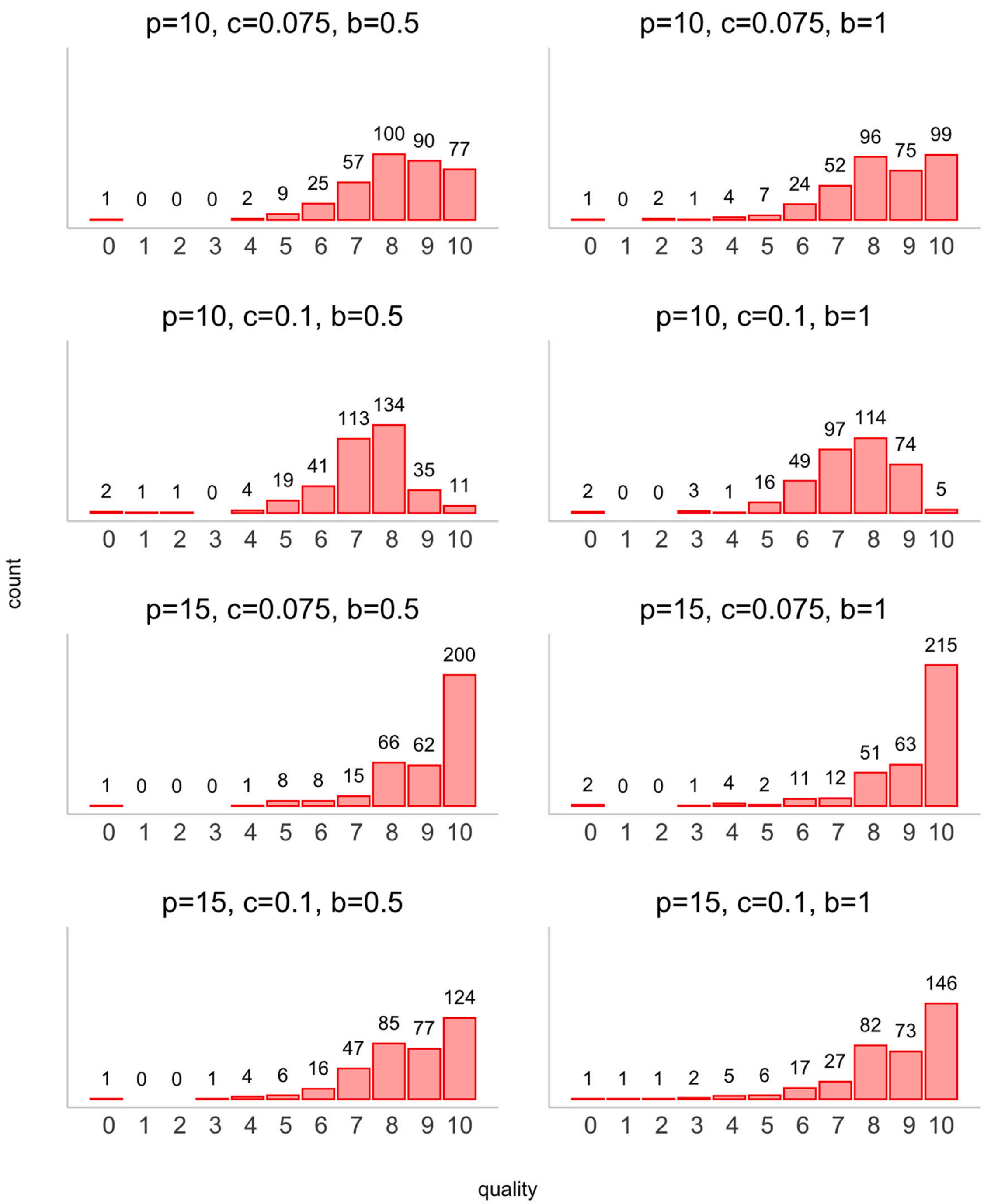

Fig. 3. Quality histograms in quadropoly.

4.2. Nonparametric estimation of altruism distribution by Bayes-Nash equilibria

We adapt a nonparametric estimation method by Guerre et al. (2000) (abbreviated to GPV) for first-price auctions. It is illustrated here with duopoly and an incentive configuration. First, we invert equilibrium strategy q^* in (9) to obtain α in terms of $q^*(\alpha)$, the utility function U, and incentive parameters:

$$\alpha = \frac{\left\{\begin{array}{c} 2cq^*(\alpha)U'(p-cq^*(\alpha)^2)\displaystyle\int_{\underline{\alpha}}^{\overline{\alpha}} S(q^*(\alpha);q^*(x))\mathrm{d}F(x) \\ -U(p-cq^*(\alpha)^2)\times \displaystyle\int_{\underline{\alpha}}^{\overline{\alpha}} bS(q^*(\alpha);q^*(x))[1-S(q^*(\alpha);q^*(x))]\mathrm{d}F(x)\end{array}\right\}}{\left\{\begin{array}{c} b\displaystyle\int_{\underline{\alpha}}^{\overline{\alpha}} S(q^*(\alpha);q^*(x))\mathrm{d}F(x) \\ +bq^*(\alpha)\displaystyle\int_{\underline{\alpha}}^{\overline{\alpha}} bS(q^*(\alpha);q^*(x))[1-S(q^*(\alpha);q^*(x))]\mathrm{d}F(x)\end{array}\right\}}. \tag{11}$$

Given equilibrium q^*, the uncertainty about a rival subject's altruism is equivalent to the uncertainty about 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 subject's equilibrium quality at α, we rewrite (11) as

$$\alpha = \frac{2cqU'(p-cq^2)\displaystyle\int_0^{10} S(q;x)\mathrm{d}G^*(x) - U(p-cq^2)\times\int_0^{10} bS(q;x)[1-S(q;x)]\mathrm{d}G^*(x)}{b\displaystyle\int_0^{10} S(q;x)\mathrm{d}G^*(x) + bq\int_0^{10} bS(q;x)[1-S(q;x)]\mathrm{d}G^*(x)}. \tag{12}$$

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^*.

The two-step GPV method is as follows. In Step 1, the densities of equilibrium quality distribution G^* are estimated by the empirical quality densities. Let $\hat{g}(x)$ denote the empirical quality densities, fractions of subjects who have chosen quality $x = 0, 1, \ldots, 10$. We use $\hat{g}(x)$ to estimate the densities of G^*. The empirical densities of the 24 games are those in Figs. 1 to 3.

The terms $\int_0^{10} S(q;x)\mathrm{d}G^*(x)$ and $\int_0^{10} bS(q;x)[1-S(q;x)]\mathrm{d}G^*(x)$ in (12) are estimated by $\sum_{x=0}^{10} S(q;x)\hat{g}(x)$ and $\sum_{x=0}^{10} bS(q;x)[1-S(q;x)]\hat{g}(x)$, respectively. For each subject $i = 1, \ldots, 361$, we use (12) to calculate:

$$\hat{\alpha}_i = \frac{2cq_iU'(p-cq_i^2)\sum_{x=0}^{10} S(q_i;x)\hat{g}(x) - U(p-cq_i^2)\sum_{x=0}^{10} bS(q_i;x)[1-S(q_i;x)]\hat{g}(x)}{b\sum_{x=0}^{10} S(q_i;x)\hat{g}(x) + bq_i\sum_{x=0}^{10} bS(q_i;x)[1-S(q_i;x)]\hat{g}(x)}, \tag{13}$$

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:

$$\hat{F}(a) = \frac{1}{361}\sum_{i=1}^{361} I\{\hat{\alpha}_i \le a\}. \tag{14}$$

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 the quality choice: for each $i = 1, \ldots, 361$, we compute

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

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

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

where $\hat{l}(x), x = 0, 1, \ldots, 10$ 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.

Subjects' maximum quality choice is 10. Some subjects could have hit a corner solution; if quality could go higher than 10, that higher value might have been chosen. We do a robustness check on this possibility. When quality 10 is chosen, we hypothesize that it could be either 10, 11, or 12, with the original density for 10 spread evenly over the qualities 10, 11, or 12. The above estimated α's would then extend to $\hat{l}(x) = 11, 12$. We perform tests on these hypothetical distributions; the results remain the same and are collected in Section C.3 of the Online Appendix.

Given preferences and a symmetric equilibrium, our Bayesian game with independent values is identified by the equilibrium quality being monotone in altruism. GPV's 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

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

valuation distribution is smooth. However, subjects in our game choose from only 11 possible qualities. We 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 a linear utility function: $U(x) = x$. Then α is the marginal rate of substitution between patient benefit bq and profit $p - cq^2$. For monopoly we have

$$\alpha = \frac{2cq}{b}, \tag{15}$$

for duopoly, we have

$$\alpha = \frac{2cq \int_0^{10} S(q;x)\mathrm{d}G(x) - (p - cq^2) \times \int_0^{10} bS(q;x)[1 - S(q;x)]\mathrm{d}G(x)}{b \int_0^{10} S(q;x)\mathrm{d}G(x) + bq \int_0^{10} bS(q;x)[1 - S(q;x)]\mathrm{d}G(x)}. \tag{16}$$

We omit the corresponding expression for α under quadropoly.

The linear U assumption is an approximation, and has been used in many previous studies, as early as in Ellis and McGuire (1986). The approximation is acceptable when income effects are insignificant. We use a random-choice payment method; only one game out of eight (in each market) is used for payment, so the variation in wealth is quite limited. Nevertheless, we can relax this. In Section C.2.1 of the Online Appendix, we present estimation results for the constant-absolute-risk-aversion (CARA) utility function $U(x) \equiv 1 - \exp(-rx)$.[11] 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 reported in Section C.4 of the Online Appendix). The drawback is that the marginal rate of substitution between patient benefit and profit varies with the profit, so the estimated value of α is not so easy to interpret.

Table 3 presents the means of the estimated α distributions in monopoly. We use these estimated monopoly means as normalization, which uses the estimated monopoly mean as the origin. In duopoly and quadropoly, for each incentive configuration, we subtract the corresponding estimated monopoly mean from each estimated α. 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.

Across each row, the average altruism has decreased from monopoly to duopoly, and then decreased further more from duopoly to quadropoly. Competition reduces altruism on average. Standard deviations also tend to be different, but the pattern is not so uniform.

Each of the α estimate is a nonlinear transformation of the chosen quality and the empirical quality distribution, and market and incentive-configuration parameters. We show the histograms of normalized α estimates with overlaid smooth densities in three markets in Figs. 4 to 6. Note that we show densities rather than counts in y-axis in these figures, unlike the quality histograms in Figs. 1 to 3.

First, start with monopoly α estimates in Fig. 4. Due to the nonlinear transformation from the observed qualities to the estimated α, the actual values differ considerably across different incentive configurations. Nevertheless, these histograms show that altruism distributions are diverse. The normalized α estimates in monopoly are in Table C.1 in Section C.1 of the Online Appendix.

[11] CARA 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 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

Next, we turn to estimated duopoly α (again normalized by the corresponding monopoly mean) shown in Fig. 5 and in Table C.2 in Section C.1 of the Online Appendix. We do not report those α when the corresponding quality was chosen by none of the subjects. The frequency for each α estimate is the same as the corresponding quality frequency, which is in Fig. 2.

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.

Fig. 6 and Table C.3 in Section C.1 of the Online Appendix present the (normalized) α estimates for quadropoly. The frequency for each α estimate is the same as the corresponding quality frequency, which is in Fig. 3. Similar to duopoly, quadropoly α distributions show a stronger concentration below the normalized monopoly mean and are left-skewed, as in duopoly.

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 perform standard two-sample Kolmogorov–Smirnov (KS) tests on the (null) hypotheses that two estimated altruism distributions 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 $\widehat{F}_1$ and $\widehat{F}_2$, their KS distance is defined by $KS_{1,2} \equiv \sup_a |\widehat{F}_1(a) - \widehat{F}_2(a)|$. We have plotted the 24 actual estimated α distributions, not normalized at monopoly mean α, in Fig. 7.

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 C.4 in Online Appendix C.1 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. Hence, 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.

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 C.5 in Online Appendix C.1 presents the KS distances for these distributions. There, pairs are labeled by the order in which they were presented in Section 3.1, 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.

Remark 4 (*Bonferroni Correction*)**.** We test many related hypotheses. It is customary to adjust the p-values to account for multiple testings; see, for example, Czibor et al. (2019). We use the Bonferroni correction to adjust the p-values. Even after the correction, the majority of comparisons (104 out of 108) remain significant at 1%. Two comparisons of α distributions in incentive configurations under monopoly, however, become significant only at 5% after the correction: ($p = 10, c = 0.1, b = 1$) vs. ($p = 15, c = 0.075, b = 1$) and ($p = 10, c = 0.1, b = 0.5$) vs. ($p = 15, c = 0.075, b = 0.5$). For the comparison ($p = 10, c = 0.075, b = 0.5$) vs. ($p = 15, c = 0.075, b = 0.5$) under monopoly, we can still reject the same-distribution hypothesis at 10%. However, for ($p = 15, c = 0.1, b = 0.5$) vs.($p = 10, c = 0.1, b = 0.5$) under monopoly, we cannot reject the identical-distribution even at 10% (the p-value is 0.1206).

[12] Whereas 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.

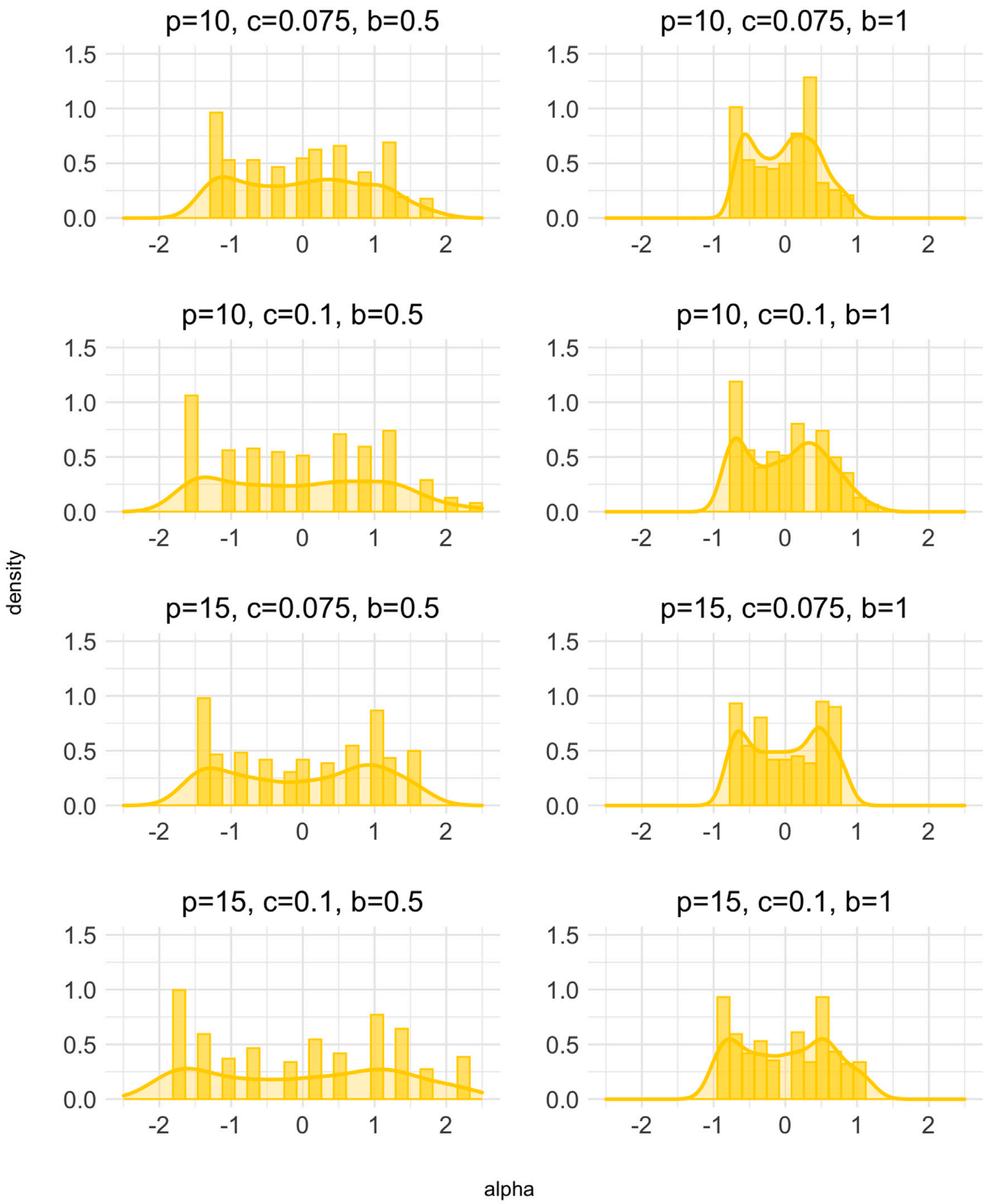

Fig. 4. Histograms of normalized estimated α in each incentive configuration in monopoly.

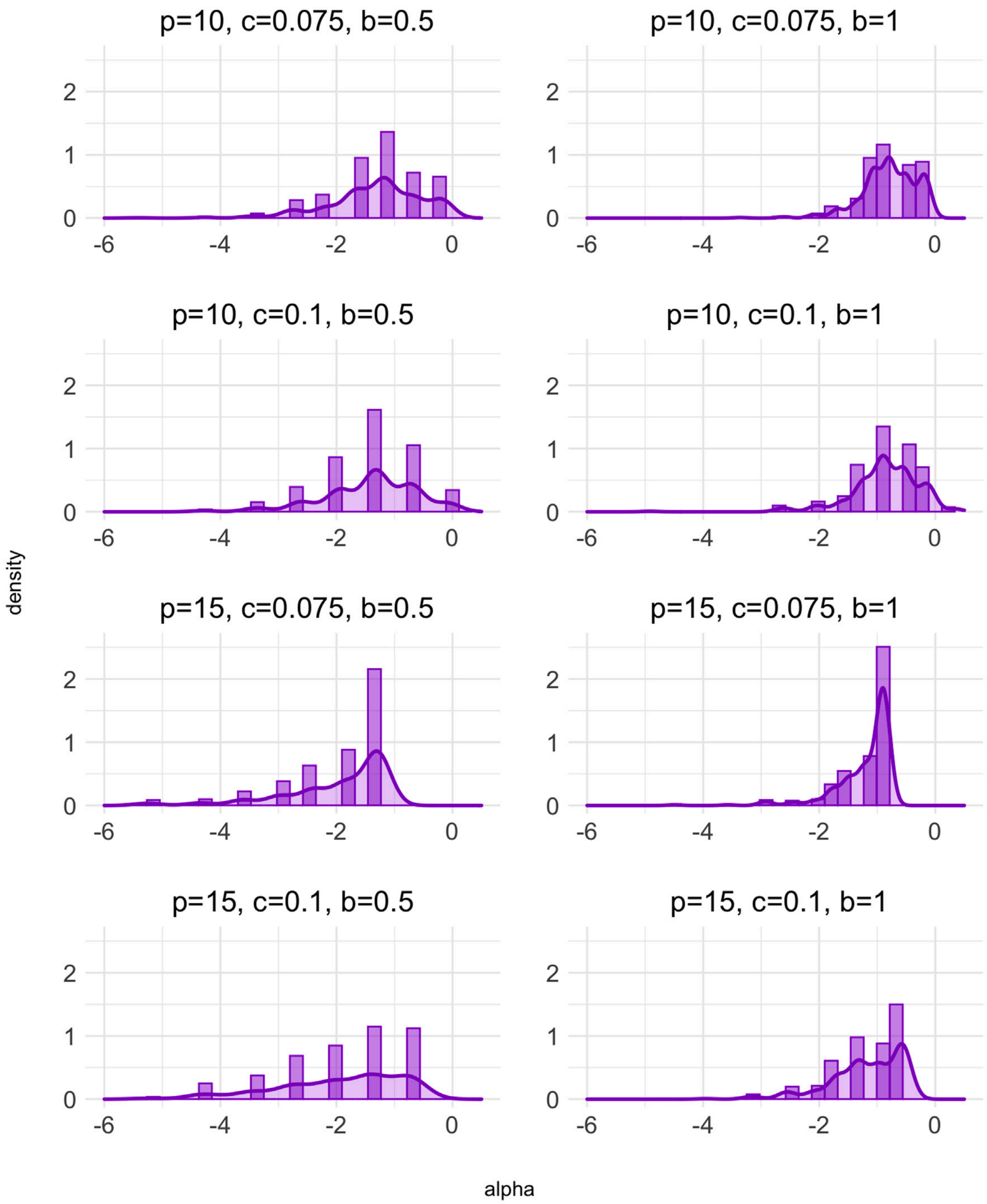

Fig. 5. Histograms of normalized estimated α in each incentive configuration in duopoly.

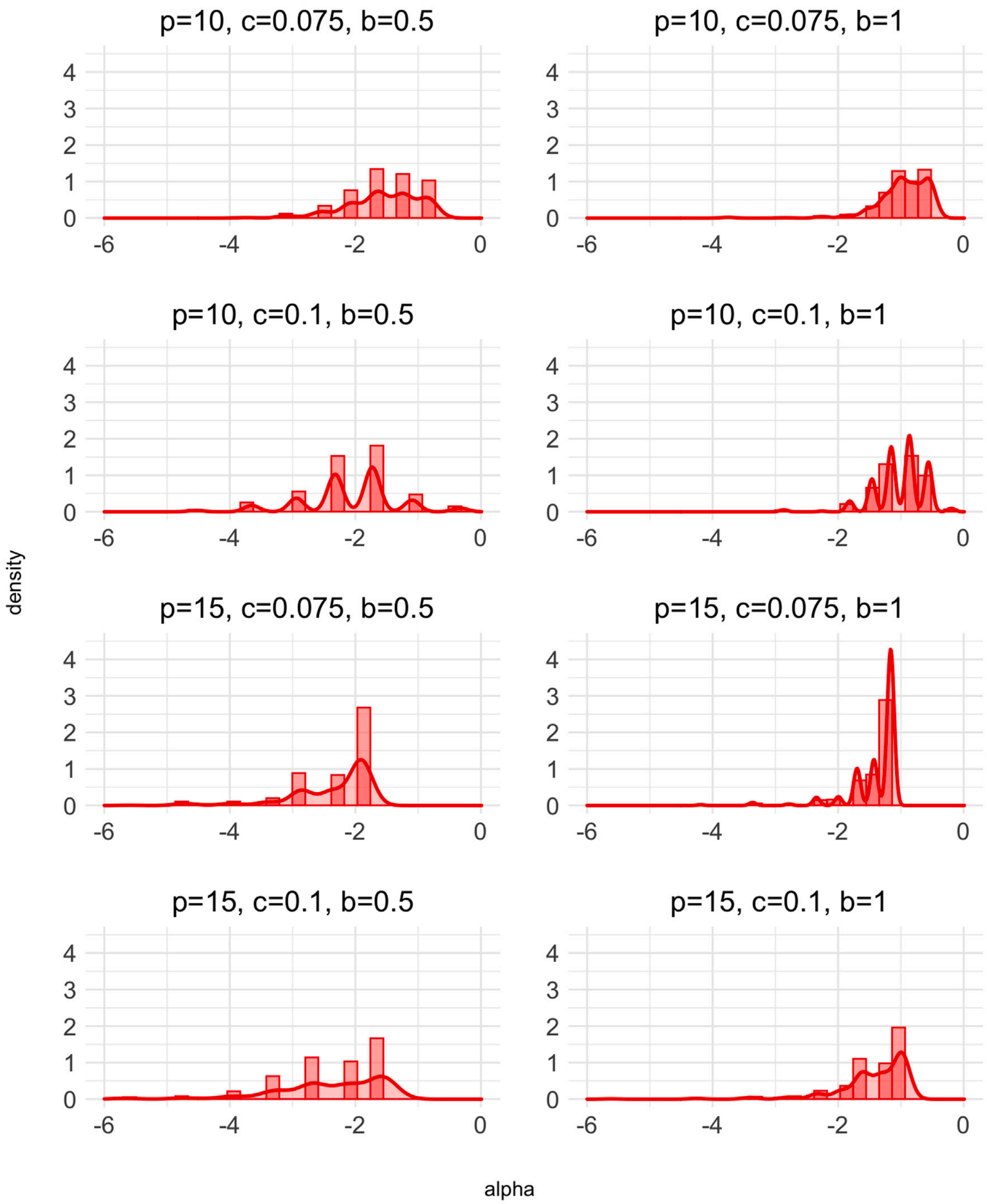

Fig. 6. Histograms of normalized estimated α in each incentive configuration in quadropoly.

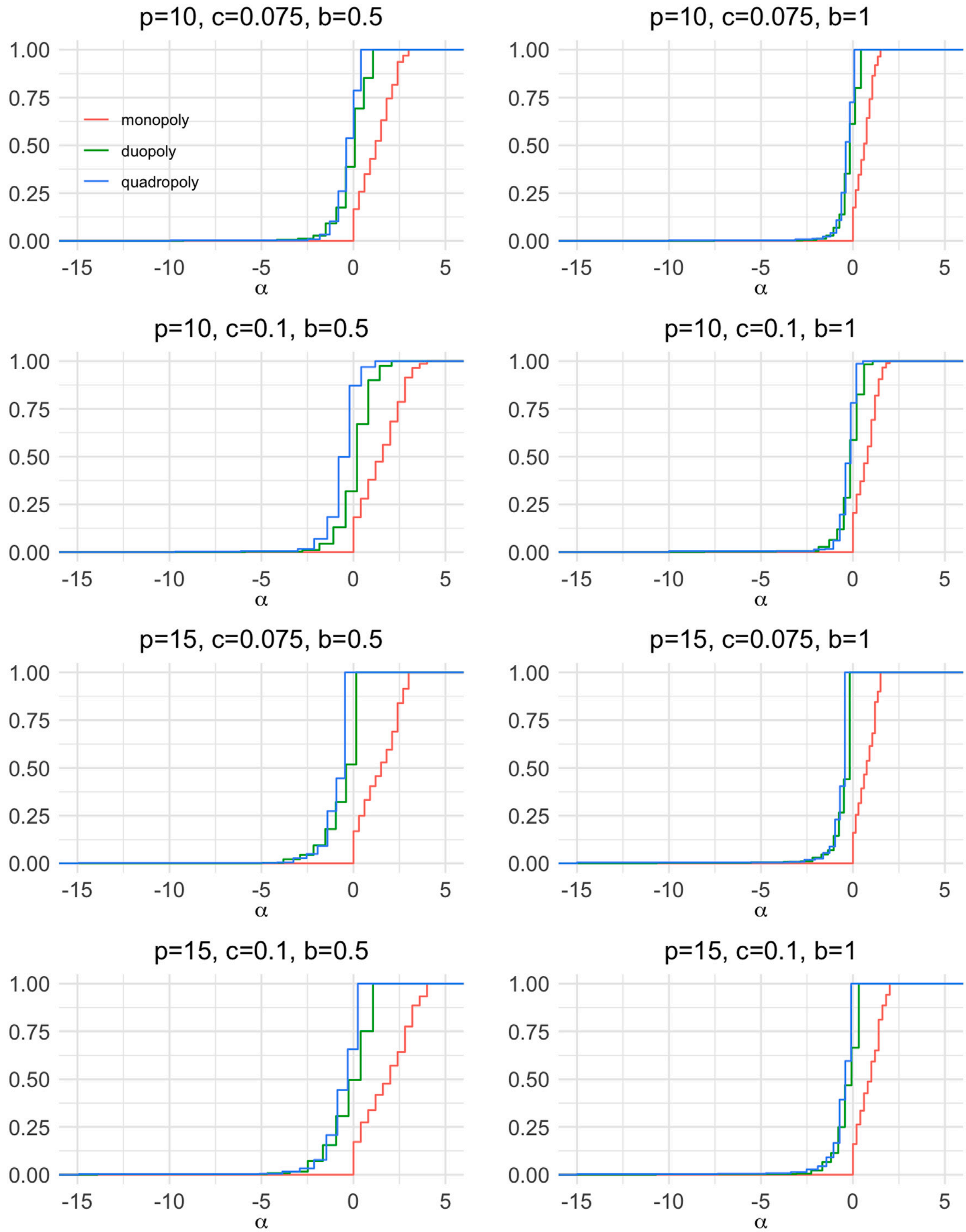

Fig. 7. Distributions of estimated α in each market and in each incentive configuration.

4.5. Counterfactual monopoly qualities from estimated duopoly and quadropoly altruism

Whereas Table 2 and Figs. 1 to 3 report the outcomes, our structural estimation of α distributions in Section 4.2 can separately identify the effects (i) due to preferences change and (ii) due to market-incentive changes. However, results in Sections 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 C.2 and C.3 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, 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.) For ease of display, we round each counterfactual quality to its closest integer.

Differences between empirical monopoly qualities and counterfactual qualities are striking. Histograms in Figs. 8 and 9 have no resemblance to those in the empirical quality distributions in Fig. 1, which are shown for comparison as yellow bars. Counterfactual results provide more evidence that the altruism distribution changes according to market competition.

4.6. Discussions of theoretical model and structural estimation

Establishing the central thesis relies on a theoretical model on preferences, a game, and an experiment, followed by structural estimation of preferences via properties of Bayes-Nash equilibria. Results should be interpreted as a constellation of particular preferences and game-form definitions together with the GPV estimation adaptation; they should not be viewed in the isolation of a single component. The actual implementation requires certain assumptions. Perhaps most important is the one that the experimental outcome is sufficiently described by a symmetric Bayes-Nash equilibrium. Two issues naturally arise. Are Bayes-Nash equilibria sufficiently good for describing the experimental outcomes? Are there many, possibly asymmetric, equilibria?

The second issue is a common concern in structural estimation of equilibria in empirical industrial organization. The usual assumption in the extant literature is that the outcome is described by *one* equilibrium, and it is not critically important which one. As long as the outcome is driven by an equilibrium, the structural estimation results are not compromised. We have implicitly adopted this convention. However, we should concede that our game may have asymmetric equilibria, which generally are intractable.[13] However, in an anonymous game in which a player's rival is drawn randomly from a population, it is awkward to suppose that a fraction play one equilibrium strategy and another fraction play another.

Now, the first issue of whether subjects exhibit equilibrium behavior is more fundamental. We do concede that this is a maintained assumption; given our data and setup, it cannot be validated externally. Also, we were not prepared to allow subjects to practice-play Bayes-Nash equilibria. This is because any learning by subjects about equilibrium play would have contaminated the within-subject design. However, we should note that our experiment had not generated random or chaotic data. In any case, structural estimation of alternative solution concepts seems uncommon; if we had abandoned Bayes-Nash equilibria, we would be unable to resolve estimation problems.

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 because our design does minimize these contaminations. 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.

5. Reduced-form analysis of experimental data

For reduced-form estimation, we begin with aggregated descriptive statistics.[14] 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, whereas cost and patient-benefit parameters vary between low and high. We record the averages of these 4 qualities for each subject, and then we find the average of all 361 subjects (the average of a total of 1444 quality choices).

[13] Here is why asymmetric Bayes-Nash equilibria are impossible to handle. Suppose that there are 10 players. In one equilibrium, 5 players are using Strategy 1, and 5 players are using Strategy 2. Consider Player 1. He faces 4 players using Strategy 1, and 5 players using Strategy 2. And in an equilibrium, Player 1 must find it optimal to use Strategy 1. Now consider Player 6. He faces 5 players using Strategy 1, and 4 players using Strategy 2. And in equilibrium Player 6 must find it optimal to use Strategy 2. In general we end up with one integral equation for Strategy 1, and then another integral equation for Strategy 2, and they have to be solved simultaneously. And this is predicated on equal numbers of players using Strategy 1 and Strategy 2. Other combinations are feasible, so it is difficult to search for asymmetric equilibria. We are unaware of any paper that structurally estimates asymmetric equilibria. For more, see Section A.2 in the Online Appendix.

[14] Table 2 already describes the 24 quality means and standard deviations for the 3 markets and 8 incentive configurations, and Figs. 1 to 3 show the quality histograms.

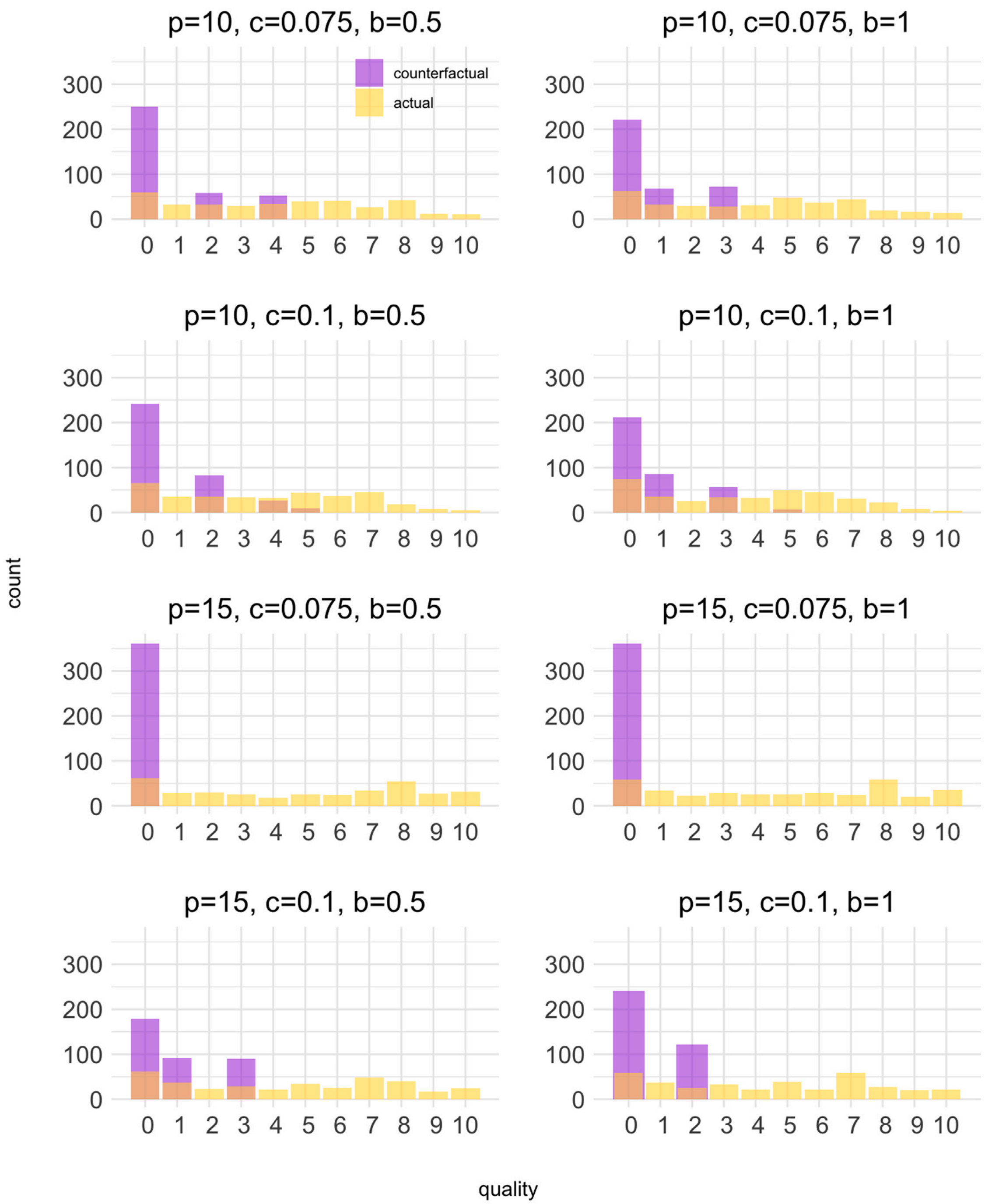

Fig. 8. Counterfactual monopoly quality histogram from duopoly altruism α.

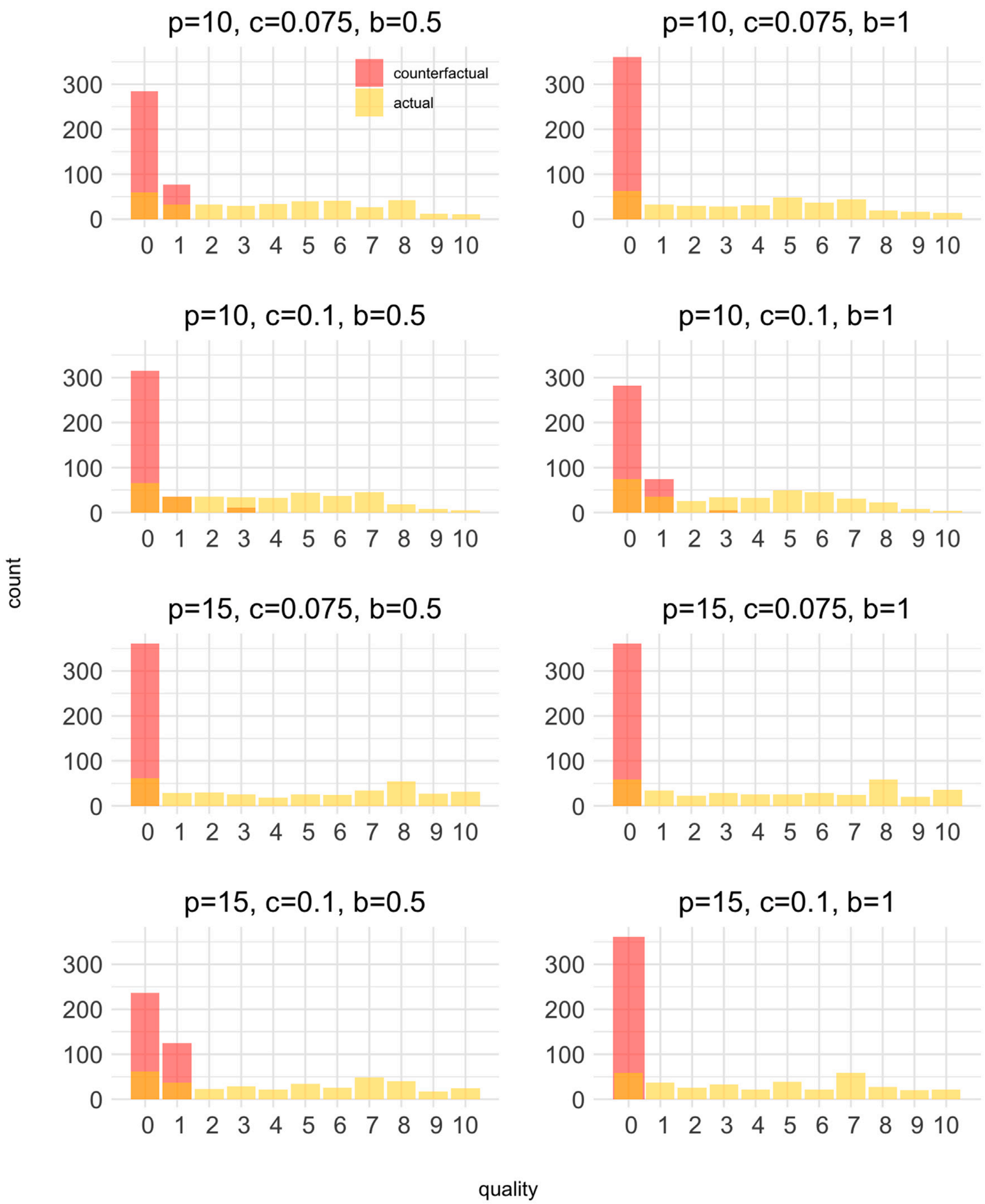

Fig. 9. Counterfactual monopoly quality histogram from quadropoly altruism α.

Table 5
Descriptives on qualities for the variations in price, costs, and patient benefit.

Parameter	Low parameter (N = 1444, per market)		High parameter (N = 1444, 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

In Table 5, 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 value, 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 5 presents the quality-choice averages for each parameter in each market.[15]

From the first three rows with data entries in Table 5, average quality is higher in each market when the price is set at the higher value, 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 value, 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.

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

$$q_i = \beta_0 + \beta_1 D + \beta_2 Q + \gamma_1 Price + \gamma_2 Cost + \gamma_3 Benefit + \psi \mathbf{X}_i + \varepsilon_i, \tag{17}$$

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 value 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. Eq. (17) 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 6 presents the estimation results. In Model (2), we add market and incentive-configuration interaction terms.

From Table 6, quality is significantly higher in duopoly and quadropoly than monopoly, and the magnitudes are similar across 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 in 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 $p < 0.001$).

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 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 data from an experiment in a health frame, we show that 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 of duopoly and quadropoly. Using experimental data, we

[15] Table 5 aggregates the information in Table 2, which contains quality-choice means and standard deviations in each incentive-configuration-market constellation.

Table 6
Quality regressions.

Model	(1)	(2)
Duopoly (D)	3.713***	3.545***
	(0.158)	(0.157)
Quadropoly (Q)	4.046***	3.987***
	(0.157)	(0.156)
High price (= 1 if $p = 15$)	0.955***	0.693***
	(0.029)	(0.050)
High cost (= 1 if $c = 0.1$)	−0.601***	−0.375***
	(0.024)	(0.046)
High benefit (= 1 if $b = 1$)	0.078***	−0.036
	(0.024)	(0.043)
Duopoly × High price		0.461***
		(0.066)
Quadropoly × High price		0.328***
		(0.061)
Duopoly × High cost		−0.348***
		(0.056)
Quadropoly × High cost		−0.328***
		(0.055)
Duopoly × High benefit		0.224***
		(0.056)
Quadropoly × High benefit		0.119**
		(0.055)
Market order and session dummies	Yes	Yes
Constant	3.971***	4.047***
	(0.400)	(0.399)
Observations	8664	8664
Subjects	361	361
R^2	0.445	0.447

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

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 theoretical model, the identification of Bayes-Nash equilibria, and the structural estimation of preference parameters all must fit together to yield our results.

Economic institutions may shape preferences just as climate, cultural-historical events, physiology, and genetics. Observations of financial incentives crowding out are decomposed into behavioral and preference changes. This paper offers a deeper understanding of the forces underlying markets and incentives.

CRediT authorship contribution statement

Undral Byambadalai: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft. **Ching-to Albert Ma:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Daniel Wiesen:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing–original draft.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2023.102808.

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