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SOCIAL RESPONSIBILITY AND FIRM'S OBJECTIVES

Michele Fioretti

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Social Responsibility and Firms' Objectives*

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Abstract

This paper shows that firms' objectives can extend beyond profit maximization. I focus on a for-profit firm that offers charity auctions of celebrities' belongings. The firm's donations affect both revenues and costs. Counterfactuals from a structural model comparing the actual donations with the profit-maximizing benchmark indicate that the firm donates beyond profit-maximization. Linking this result to a change in the capital structure, I demonstrate that the firm's objectives include both profits and donations. I also estimate a modest increase in consumers' willingness to pay due to donations, suggesting that demand cannot explain firms' investments in social responsibility.

JEL classifications: L21, D64, C14

Keywords: objectives of the firm, profit maximization, corporate social responsibility, donations, structural estimation, externalities

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1 Introduction

The economic literature has gradually changed its vision of the consumer, who is now increasingly considered as having some type of social preferences such as altruism. In contrast, the perception of the firm's objective has seen very little evolution. The firm is typically modeled as maximizing profits. This assumption drives most of the standard results on the functioning of markets, and it also allows researchers to recover costs or supply curves (e.g., [Olley and Pakes, 1996](#), [De Loecker et al., 2016](#)).

There are many reasons to believe that firms do not maximize profits. On the one hand, managerial costs ([Ellison et al., 2016](#), [Della Vigna and Gentzkow, 2019](#)) and behavioral biases ([Ellison, 2006](#), [Hortaçsu et al., 2019](#)) can constrain a firm's decisions. On the other hand, firms may not limit themselves to pursue market value, as, more broadly, shareholders' welfare often directs firms' decisions as well (e.g., [Hart and Zingales, 2017](#)).

In this paper, I provide evidence that some firms are not simple profit maximizers. I study the strategic decisions of a for-profit firm, Charitystars, which offers online charity auctions of celebrities' belongings.¹ In each auction, the firm donates a fraction of the transaction price to a charity. The fraction donated is decided by the firm and the provider of the item – mainly the charity itself, a connected celebrity or individual. Both the fraction donated and the charity are known to consumers.

This environment offers several advantages to empirically identify the firm's objectives. First, the fraction donated reflects how socially responsible the firm is in each auction. This type of social responsibility is directly measurable and salient to consumers. Second, costs are observed because the firm always sets its reserve price to cover the cost of procuring the item, which depends on the donation. Therefore, this is an ideal setting to measure how social responsibility impacts profits.

I find that Charitystars does not set its donation according to profit maximization. After building and structurally estimating a tailored model of demand and supply, I show that Charitystars's average donation (70% of the transaction price) is much larger than the profit-maximizing donation (25%). The firm could more than double its profits by behaving optimally. After ruling out alternative potential explanations, I exploit a change in Charitystars's capital structure to argue that the firm's objectives are not limited to profits, but extend to donating to charities.

Methodologically, Charitystars faces a tradeoff between (i) increasing the fraction donated to stimulate demand by altruistic bidders and get better acquisition costs from

¹With offices in London, Milan, and Los Angeles, Charitystars is a for-profit start-up with almost \$4m in equity. Since its foundation in 2013, the company generated over \$10 million for charities and nonprofit organizations. For more information, see www.charitystars.com.

donors, and (ii) decreasing the fraction donated to increase the profit from each auction. Without a structural model, I show evidence that this tradeoff exists. However, since the elasticities of demand and acquisition costs to donations are unobservable from data alone, I build a structural model to evaluate the firm's objectives quantitatively. The model exploits variation in the fraction donated to estimate both how consumers' willingness to pay and procurement costs vary with social responsibility.

On the demand side, I model bidders' utility as a function of their private values for the item and their prosocial preferences (e.g., [Goeree et al., 2005](#), [Engers and McManus, 2007](#)). I envision consumers as impure altruistic bidders who derive utility both from their donations and from the donations of others ([Andreoni, 1990](#)). Theoretically, I show that the presence of altruistic consumers does not necessarily grant greater revenues to the firm. For instance, if bidders derive large utility from somebody else's donations, transaction prices can decrease when the auctioneer donates more because high-value bidders shade their bids to let other bidders win the auction. To quantify how preferences impact prices, I show that cross-auction variation in the fraction donated nonparametrically identifies the model under the restriction that a bidder's consumption value for the item is independent of the fraction donated. I test and do not reject this restriction in the data.

The model fits the data well, with estimated expected revenues within 10% of the realized ones. Prices on Charitystars command only a small premium as bidders' willingness to pay increases with the fraction donated. At the same time, donations carry a high direct cost in terms of foregone revenues: a counterfactual scenario where the firm does not donate quantifies the loss in net revenues to be as large as €260 per listing, or about 70% of the average transaction price. Thus, looking only at the demand side, the firm would be better off by running regular non-charity auctions.

Turning to the supply side, the firm purchases the item from providers (mainly charities and celebrities) previous a payment, and contracts on the fraction of the auction price to be donated back to the charity. To estimate how the procurement cost varies with the fraction donated, I exploit a piece of information provided directly by advisors of the firm: the firm sets the reserve price to break-even. I find that procurement costs decrease in the fraction donated, implying negative marginal costs, and explain this result with a bargaining model. The estimation shows that the optimal donation is about 25% of the transaction price, yet the average donation in the data is 70%, indicating that Charitystars is far from a pure profit maximizer.

This finding points to donations as an additional objective of the firm. Using empirical and anecdotal evidence, I rule out potential alternative explanations such as biased beliefs on bidders' willingness to pay, and reputation-building. Then, I exploit the entry of a

venture fund in Charitystars's equity to corroborate my claim. Although the entry did not imply a change in management, the average donation dropped from 70% to 50% after the entry. Because the fund entered for a capital gain, it stirred the company towards better profitability, inducing a shift in objectives. To rationalize the large pre-entry donation, Charitystars's objective function should weigh its profits 60% and its donations 40%. This finding is in line with recent results in the finance literature showing that socially responsible actors invest in social impact firms despite being less profitable (Riedl and Smeets, 2017, Barber *et al.*, 2019).

Relation to the Literature. Several related research papers support my conclusions on both revenues and costs. On the revenue side, I estimate modest price elasticities of the order seen in other papers studying bidder's behavior in charity auctions (e.g., Elfenbein *et al.*, 2012). Given how salient are Charitystars's donations for consumers, my findings suggest that consumer demand cannot explain firms' prosocial inclinations. In the same vein, looking across more than 400 US companies, Gartenberg *et al.* (2019) finds that a firm's sales do not correlate with its social purpose. On the cost side, giving is profitable because it changes Charitystars's cost-structure as its money-making ability and ethical concerns are not separable. Quoting Hart and Zingales (2017), if consumers and investors value charitable donations, why "would they not want the companies they invest in to do the same?" Socially responsible shareholders may see this company as an opportunity to sustain their donations over time while even receiving dividends. Under this logic, Charitystars cares not only about its profitability but also about its total giving.

The evidence that social responsibility is conducive to higher economic or financial return is sparse. Although Eichholtz *et al.* (2010) find a substantial price premium for energy-efficient buildings, a meta-analysis of over 160 papers finds only a small positive correlation between investments in corporate social responsibility (CSR) and profits, and suggest that causation may well flow from profits to CSR (Margolis *et al.*, 2007). A reason for these conflicting views lies in studying the relation between CSR and profits across firms, rather than within a firm: not only the decision to adopt CSR may well depend on unobserved firm-specific factors (Bénabou and Tirole, 2010), but also CSR activities are considerably heterogeneous, complicating comparison across firms (Chatterji *et al.*, 2009, Kotsantonis and Serafeim, 2019). Moreover, this variation may interact in surprising ways, sometimes reducing a firm's perceived social impact by, for example, disseminating misleading information of environmental friendliness (Lyon and Maxwell, 2011) and by giving to charities to influence connected congress members (Bertrand *et al.*, 2018).

My findings suggest that addressing whether CSR increases profits by comparing firms' outputs may lead to inconclusive results if firms choose suboptimal levels of social

responsibility. Rather than comparing across firms, I avoid these issues by studying how a firm's social responsibility strategy departs from the profit-maximizing one. At the same time, I test a causal link between profitability and social responsibility through the lenses of a theoretical model of a firm that sells to socially-oriented consumers (e.g., [Baron, 2001](#), [Bagnoli and Watts, 2003](#), [Besley and Ghatak, 2007](#)). My findings strongly indicate that consumers do not react substantially to socially responsible campaigns, even in an environment where social responsibility is especially salient. Therefore, demand concerns seem unlikely to stimulate firms to invest in CSR.

This paper is also related to a growing literature investigating firms' conduct. For example, [Duarte et al. \(2020\)](#) find that Italian cooperatives behave in the same manner as their for-profit competitors. On the other hand, [Macchiavello and Miquel-Florensa \(2019\)](#) also show that coffee intermediaries pay Colombian coffee farmers more than what implied by profit maximization, but explain this finding through resale price maintenance policies rather than fair trade or social responsibility. Principal-agency problems between shareholders and management (e.g., [Hart, 1995](#), [Liljeblom et al., 2011](#)) and managerial quality (e.g., [Bloom and Van Reenen, 2007](#), [Goldfarb and Xiao, 2011](#), [Adhvaryu et al., 2018](#)) are other classic reasons why firms fail to maximize profits.

Suboptimal choices are also observed in the National Football League as certain plays called by coaches do not maximize the probability of victory ([Romer, 2006](#)), and teams often waste their top picks at the annual draft ([Massey and Thaler, 2013](#)). These papers speculate that influence from shareholders and fans could sway decisions away from optimality. However, supporting empirical evidence using business data is lacking. This paper fills this gap by demonstrating that firms can be influenced by concerns that are external to profits.

2 Auctions on Charitystars

Charitystars is a for-profit internet company helping charities do fundraising, by offering charity auctions of celebrities' memorabilia. Charitystars auctions a very broad spectrum of items, from VIP tickets to sport events to arts collectibles.² Soccer is one of the most popular item categories with over 4,000 auctions held in 3 years. Moreover, Charitystars is a de facto monopolist in the market for actually worn soccer jerseys, on which I focus.³

²Charitystars is owned by its funding members, who also are managers in the company, and other investors including funds.

³It is possible to find some worn soccer jerseys on eBay as well, but this marketplace is much thinner compared to Charitystars. Moreover, as it will be shown in Section 6.3, bidders pay a charity premium on Charitystars, meaning that Charitystars bidders would lose money in case of resale.

Auction Format. On Charitystars, the auction winner wins the auctioned item and pays his bid. The transaction price is then shared between Charitystars and a charity according to a known sharing rule. The charity receiving the donation, as well as the fraction donated, are known to all bidders before the auction. Donations are guaranteed by issuing certificates.

All Charitystars's auctions involve a single item and employ an open, ascending-bid format analogous to eBay. Bidders can also submit cutoff bids instead of a bid. Once a cutoff is set, Charitystars will issue a bid equal to the smallest of the standing price and the highest submitted cutoff price, plus the minimum increment. Importantly, the auction countdown is automatically extended by 4 minutes anytime a bid is placed in the last 4 minutes of the auction. This effectively impedes sniping (Backus *et al.*, 2017). After each sold soccer jersey, if a fraction q of the transaction price is donated, the firm keeps $1 - q$ of the price paid as net revenues.

All items are posted online on the firm's website and advertised on the social media of the firm in a similar fashion. The listing webpage shows pictures of the item on the left of the screen. Bidders find a short description on the bottom of the page, together with the information on the recipient charity. A picture of a typical webpage at the time of the data collection is in Appendix Figure D1.

Procurement. Charitystars procures the memorabilia mostly from footballers, teams, and charities. The fraction donated is bargained between the firm and the provider of the item, who also requires a payment for procuring the item. Therefore, charities procuring the item receive both a fixed fee and a fraction donated. Charitystars's minimum fee is 15% of the transaction price, and increases if the provider requires a larger compensation to provide the item (see Appendix Figure D2). Importantly, talks with advisors and shareholders of the firm revealed that the firm sets the reserve price in soccer jersey auctions such that the portion of the reserve price that is kept by the firm equates procurement costs. Due to the complexity of setting the profit optimal reserve price, this simple scheme allows avoiding losses.⁴

Data. I use publicly available data from Charitystars.com. The dataset is collected from the website and contains auctions of authentic soccer jerseys sold between July 1, 2015 and June 12, 2017 (1,583 auctions). I focus on this period because it represents two consecutive football seasons. Figure 1 reports the number of auctions for each percentage donated. All auctions where the fraction donated is higher than 85% are disregarded as they coincide with special events. Throughout the paper, I let q denote the fraction donated.

For each auction, I observe all bids placed, the date and time of the bid, the bidder

⁴The reserve price is not disclosed on the website. However, it is displayed in the HTML code of the webpage. Whether bidders know the reserve price does not affect the analyses in the paper.

nationality, and the charity. I do not observe the auction start date, and I proxy the auction length as the days between the first bid posted and the closing day.⁵ I focus on listings of sold items with at least two bidders, transaction prices in the range €100 - €1,000, and with a minimum raise not larger than €25 (1,109 auctions in total). The average minimum increment is less than €2.00, and the transaction price is greater than the reserve price in more than 95% of the listings. On average (median) the winning bid is 2.9 (2) times larger than the reserve price. All the variables are defined in detail in Appendix B and Appendix Table B1 display summary statistics for the main variables.

3 The Impact of Giving on Bidding: Empirical Evidence

The reduced form evidence in this section provides the foundation for modeling demand in later sections by illustrating how giving impacts prices and competition across bidders.

Intensive Margin. I first investigate whether greater transaction prices are associated with more generous donations (q). To test this hypothesis, I run a set of regressions where the transaction price is on the left-hand side and auction characteristics, including q , are on the right-hand side. Table 1 displays results from the following OLS regressions

$$price_t = \gamma_0 + \mathbf{x}_t \gamma + \gamma_q q_t + \varepsilon_t, \quad (3.1)$$

where t indexes the auctions. The vector of covariates, \mathbf{x} , includes all variables other than the fraction donated, q . The columns of the table vary based on the definition of \mathbf{x} , which appears displayed in the bottom panel of the table. The jerseys are quite comparable across different fraction donated as the latter variable is not correlated with the quality of the player wearing the auctioned jersey.⁶ The estimates indicate that a 0.1 increase in q , is associated with a price increase between €8.4 and €9.4, or 2.9% of the average price. This result points to a positive but small correlation between bids and donations.

Since the fraction donated is bargained between the provider of the item and Charitystars, $\hat{\gamma}_q$ could be inconsistent if unobserved characteristics of the item affect both bidders' valuations and the bargaining outcome (q). In this case, Table 1 could erroneously suggest that bidders care for giving, while they only care for the unaccounted characteristics.

To account for endogeneity, I instrument a listing's reserve price and q with the average

⁵The average length of Charitystars's auctions is usually between 1 and 2 weeks.

⁶To check whether jerseys worn by better players are associated with larger fraction donated, I downloaded player data from the FIFA videogames on the previous 5 years and checked the correlation between q and the overall player quality. The correlation is only between -0.07 and 0, excluding this channel. The correlation between q and the other covariates is also small (lower than |0.25|).

q and the average reserve price across all concurrent auctions ending within ± 5 days. The instruments are valid if the concurrent auctions are not correlated after controlling for covariates. Identification would fail, for instance, if a charity procures several items for an advantageous deal. This occurrence is accounted for by exploiting the connection between a charity and a specific footballer or team. In particular, I control for the number of listings of jerseys from the same team in the previous three weeks and for the same player in the previous two weeks, as well as a charity counter. Hence, potential correlations across auctions are likely purged from the residual variation. Furthermore, I also control for the importance of the match (e.g., a final), player quality, and charity characteristics.

Appendix Table C2 reports the OLS and the IV estimates. The instruments strongly predict transaction prices, and the hypothesis of weak-instrument is rejected at 0.1% level across all columns. I include the average number of bidders across concurrent auctions (within 5 days) as an additional instrument for over-identification. The Sargan test does not reject the null hypothesis. The IV estimates are statistically significant and slightly larger than the OLS ones, but less precise.

I also investigate whether the relation between the logarithm of prices and the fraction donated is linear with a series of quantile regressions in Appendix Table C1.⁷ The null hypothesis that the coefficients computed at different quartiles are the same to the OLS one is not rejected at common values (F test p-value 0.82), suggesting a small and linear relationship between q and log prices.

In conclusion, bidders seem to react to donations. In particular, a 10% change in the average fraction donated results in about a 9.2% change in transaction prices. Related papers found qualitatively comparable results. For example, [Elfenbein and McManus \(2010\)](#) estimated that prices in eBay charitable listings are, on average, 6% larger than comparable non-charity ones, while within a controlled experiment [Leszczyc and Rothkopf \(2010\)](#) determined that a 40% donation leads to a 40% price increase.

Extensive Margin. Bidders do not seem to prefer more generous auctions. In the data, a total number of 2,247 bidders compete on average in 5.34 different auctions. This average increases to 8.51 after excluding bidders who bid in only one auction. More than 80% of the bidders that place at least two bids, bid at least in two auctions with different fractions donated. The raw data show no correlation between the number of bidders joining an auction and q (Spearman correlation: 0.086).

I further investigate the impact of q on the extensive margin of giving with the following

⁷Appendix Figure D3 plots the coefficients.

Poisson regressions

$$\log(\mathbb{E}[\textit{number of bidders}_t | \mathbf{x}_t, q_t]) = \gamma_0 + \mathbf{x}_t \gamma + \gamma_q q_t + \log(\textit{length}_t) + \varepsilon_t,$$

where t indexes the auctions. The variable *length* is the exposure variable and tells how many days the auction lasted. Table 2 reports the estimated coefficients which should be interpreted in terms of number of bidders per day. The results confirm the absence of a correlation between q and the number of bidders. This conclusion is also reaffirmed when instrumenting q as previously done (Appendix Table C3).

Asymmetric Bidding. Before moving to the auction model, I show that the data fail to portray significant asymmetries in the way bidders bid within an auction. There are two main asymmetries that can be inspected. First, as most jerseys belong to Italian teams (63% of the auctions) and most charities are Italian (90% of the auctions), bidders from different nationalities could employ different bidding strategies. However, Appendix Table C6 shows no effect of a winner’s nationality on prices. Second, some bidders can be collectors of jerseys and may care less about donating. I define collectors as recurrent winners who won more than the median number of auctions won (three). Table C7 in Appendix C shows that recurrent winners do not pay more on average. Therefore, in the next section I study the behavior of symmetric bidders by modeling Charitystars’s auctions and in Sections 5 and 6 I show how to identify and estimate the primitives of such model.

4 Demand Model: Altruism in Charity Auctions

A charity auction entails the donation of a portion of the transaction price to a charity. If bidders care for charitable giving, their utility should also include how much is earned by the charity. In this section, I extend the seminal work on price-proportional auctions by Engelbrecht-Wiggans (1994) and Engers and McManus (2007) to fit the main characteristic of Charitystars’s online auctions, namely that only a fraction $q < 1$ of the final price is donated. In this setting, I study both the optimal bidding strategy and the revenue-maximizing choice of q .

I model the additional utility from donating to a charity by $\beta \cdot q \cdot \textit{price}$, where β transforms the fund raised, $q \cdot \textit{price}$, in utils. Hence, β indicates the satisfaction from winning the auction and donating. Though losing bidders do not consume the item, and so receive no consumption utility, they enjoy the fact that the charity gets funded. The reward to the losing bidders is modeled by the term $\alpha \cdot q \cdot \textit{price}$. As charitable motives cannot explain the full amount of one’s bid, the literature assumes that $\alpha, \beta \in [0, 1)$. Therefore, the

realized utility to a bidder who values the private good v can be summarized by

$$u(v; \alpha, \beta, q) = \begin{cases} v - b + \beta \cdot q \cdot \text{price}, & \text{if } i \text{ wins,} \\ \alpha \cdot q \cdot \text{price}, & \text{otherwise.} \end{cases} \quad (4.1)$$

Despite its simplicity, the model implies different underlying rationale for giving depending on the relative size of α and β . Appendix Table C8 summarizes the most common theories of altruism.

The null hypothesis is that bidders are not interested in giving. If $\alpha = \beta = 0$, the classic textbook equilibrium applies, and altruistic preferences in no way shape bidding. Bidders are purely altruistic when their utility does not depend on the identity of the donor, or when $\alpha = \beta > 0$. In this case, they are solely moved by their compassionate concern for the activities of the charity (Ottoni-Wilhelm *et al.*, 2017).⁸

Selfish motives may also be present. For instance, bidders may take pride in donating (e.g., Andreoni, 1990, Fisher *et al.*, 2008). In this case, $\beta - \alpha > 0$ implies that bidders receive a “warm glow” when winning and donating. An extreme case is when bidders only care for their donations and have no intrinsic motivations ($\beta > 0$ but $\alpha = 0$). This model captures the role of social status or prestige in donation (e.g., Harbaugh, 1998).⁹

Leszczyc and Rothkopf (2010) provide empirical evidence for $\alpha > \beta > 0$ using a field experiment with manipulated charity auctions to assess overbidding. In such a “volunteer skill” model, bidders derive more utility from others’ contributions than their own.

4.1 How Donations Impact Bids and Revenues

To find the optimal fraction donated for the auctioneer, knowledge of how demand varies with q is necessary. Thus, I start by examining a bidder’s optimal bidding strategy as a function of q . The following standard regularity assumption is maintained throughout.

Assumption 1. *Regularity:*

1. All $n > 1$ bidders have private and independent values for the auctioned item. Values are drawn from a continuous distribution $F(\cdot)$ with density $f(\cdot)$ on a compact support $[\underline{v}, \bar{v}]$;
2. The hazard rate of $F(\cdot)$ is increasing.

⁸A theoretical treatment of these auctions first appeared in Engelbrecht-Wiggans (1994), who analyzed auctions with price-proportional benefits to bidders (all bidders receive an equal share of the final price).

⁹ $\beta > 0, \alpha = 0$ is consistent with bidders receiving subsidies as is common in timber auctions (Athey *et al.*, 2013).

The independent private value assumption is relaxed in the estimation by the inclusion of auction heterogeneity, which effectively allows for affiliated values. An alternative would have all bidders valuing the jersey equally, but enjoying only imperfect signals of this value before bidding. Under such a common values scenario, the winner's course increases in the number of bidders. As a result, bidders will shade their bids the more bidders join the auction. However, this prediction is refuted by the positive and significant coefficients of the number of bidders in Table 1. Condition 2. of Assumption 1 ensures the existence of a unique global optimum of the bidding function and it is important for the identification of the primitives of the model $\{F(v), \alpha, \beta\}$.

Optimal Bid. Due to the strategic equivalence between ascending and second-price charity auctions (Engers and McManus, 2007), the expected utility to a bidder with value v in a second-price charity auction is

$$\begin{aligned} \mathbb{E}[u(v; \alpha, \beta, q)] = & \underbrace{\mathbb{E}[v - (1 - q \cdot \beta) \cdot price, i \text{ wins}]}_{i \text{ wins and pays price}} + \underbrace{q \cdot \alpha \cdot price \cdot \Pr(i\text{'s bid is } 2^{nd} \text{ highest})}_{i \text{ loses and bids } b_i = price} \\ & + \underbrace{q \cdot \alpha \cdot \mathbb{E}[price, i\text{'s bid is } < 2^{nd} \text{ highest}]}_{i \text{ loses and } price > b_i}, \end{aligned}$$

where, $price$ denotes the second-highest bid as this is the price at which the second-highest bidder drops out of the auction. The expected utility is taken over three mutually exclusive events. In the first brackets the bidder wins the contest, pays the price, enjoys v and additional utility from giving to the charity ($\beta \cdot q \cdot price$). In the second and third brackets, the bidder either drops out as a second-highest bidder or earlier. In either case, the bidder benefits in proportion to the expected donation ($\alpha \cdot q \cdot$ expected price).

Focusing on the symmetric Bayesian Nash equilibrium of the second-price auction game, the equilibrium bid for a bidder with private valuation v and charitable parameters α and β in a symmetric second-price charity auction where the auctioneer donates q is

$$b^*(v; \alpha, \beta, q) = \begin{cases} \frac{1}{1+q \cdot (\alpha - \beta)} \left\{ v + \int_v^{\bar{v}} \left(\frac{1-F(x)}{1-F(v)} \right)^{\frac{1-q \cdot \beta}{q \cdot \alpha} + 1} dx \right\}, & \text{if } \alpha > 0 \text{ and } q > 0, \\ \frac{v}{1-q \cdot \beta}, & \text{if } \alpha = 0 \text{ or } q = 0. \end{cases} \quad (4.2)$$

This bid function is also optimal in ascending online auctions: in equilibrium a bidder with value v drops out of the auction when $price \geq b(v; \alpha, \beta, q)$. Although there is no discontinuity as α goes to 0, the second line of equation 4.2 implies that truthful bidding is optimal when $q = 0$ or $\alpha = 0$ as in second-price auction with non-charitable bidders.

Therefore, this model includes the classic textbook second-price auction model.

Comparative Statics on q . Does greater fraction donated necessarily increase bids? From equation 4.2 this is true if $\alpha = 0$. In this case, a marginal increase in q is equivalent to a marginal increase in β , implying greater satisfaction from winning the auction, leading to greater bids. More generally, whether bids increase or decrease with q depends on the model of giving, as shown in the following lemma.

Lemma 1. *Bids are*

- increasing in q if $\beta \geq \alpha$;
- decreasing in q in the interval $(\tilde{v}, \bar{v}]$, where $\tilde{v} \in [\underline{v}, \bar{v}]$, if $\alpha > \beta$.

Proof. See Appendix A.2.

Under warm glow ($\beta \geq \alpha$) all bidders revise up their bids if q increases. The solid line in Figure 2a depicts this case. The dotted and dashed lines instead refer to the derivative of bids w.r.t. q for the voluntary skill model ($\beta < \alpha$): bids increase for bidders with low values, and increase for bidders with high values.

Due to the monotonic bidding strategies, bidders with high values are possible winners of the auction. A marginal change in q has two effects if α is large enough. First, it intensifies the degree of substitution between winning the auction and gaining from somebody else's contribution to the charity (Bénabou and Tirole, 2006). The substitution effect is more significant for high-value bidders, and so they are the ones to revise their bids down.

Second, low-value bidders affect their payoff only when they rank as the second-highest bidder. Thus, as their bid is complementary to that of a bidder with higher valuation, they raise their bid in the hope of extracting more surplus from the winner. A comparison of the dotted and dashed lines in Figure 2a supports this idea: more low-value bidders increase their bids when they believe they are more likely to rank high in the auction. This belief increases with the variance of the distribution of private values (dotted line).

Therefore, in a charity auction, optimal bids must balance not only the intensive margin (a bidder's surplus) with the extensive margin (the probability of winning) but also an additional margin representing free-riding.

Net Revenues and q . If the cost of procuring the item is sunk, a profit-maximizer auctioneer should set the fraction donated to maximize net revenues, or $(1 - q)$ times price.

The revenue-optimal fraction donated q_R depends on the demand parameters $\{F(v), \alpha, \beta\}$. In particular, when $\alpha = 0$, increasing q does not increase net revenues to the auctioneer, because the term $q \cdot \beta \cdot price$ act as a discount factor. Net revenues are lower than non-charity auction revenues, and the auctioneer should not donate.

Charity auctions are more appealing to the auctioneer in case of cross-bidders external-

ities ($\alpha > 0$).¹⁰ However, α should be small enough to prevent high-value bidders from excessively shading their bids. The next proposition determines the fraction donated, q_R , that maximizes net revenues.

Proposition 1. Define $\eta(p^e, q) = \frac{\partial p^e}{\partial q} \frac{q}{p^e}$ as the elasticity of the expected price, p^e , to the donation, q . When $\alpha = 0$, the auctioneer should not donate. When $\alpha > 0$, the revenue maximizing donation solves $\eta(p^e(q_R), q_R) = \frac{q_R}{1 - q_R}$.

Proof. See Appendix A.3.

Intuitively, net revenues first increase as the auctioneer increases q , reach a maximum, before decreasing to zero for $q = 1$, in which case the auctioneer donates all he or she makes. Net revenues have an inverted-U shape, which is maximized at q_R . The ratio $q/(1 - q)$ is the ratio of what is donated to what is kept and is convex in q . The firm will increase its donation rate until the marginal benefit from higher bids ($(1 - q)\eta$) equates the marginal cost from donating an extra euro (q). This is evident from Figure 2b, where net revenues (right axis) are optimized at the q that sets $\eta = q/(1 - q)$.

The Role of Externalities. The previous theoretical exercises should be read in light of the lack of agreement in the empirical literature assessing the effect of donations on prices and revenues in charity auctions. For instance, Leszczyc and Rothkopf (2010) attributed the widespread overbidding in their experimental charity over non-charity auctions to significant externalities. However, their conclusion that $\alpha > \beta$ implies higher revenues is only partially correct as it also requires enough incentives for low-value bidders to place high bids, as shown in Figure 2a. This seems to be the case in their data as their auctions averaged less than four bidders, and so low-value bidders have high chances to set the price. In contrast, another field experiment with more than 15 potential bidders in each auction found charitable prices to sink below non-charity ones at a school charity auction (Carpenter et al., 2008). Given Proposition 1, this can be explained in terms of high externalities as parents (bidders) may care more for the fundraising of the school than their donations.

Because of the central role played by the different models of giving in determining auction outcomes, the next section shows how to identify both the consumption, $F(v)$, and altruistic preferences, α and β .

¹⁰The result on the auctioneer's surplus mimics how donations impact bidders' surplus. When $\alpha = 0$, the expected bidders' surplus in a charity and non-charity auctions are the same. Thus the auctioneer cannot extract additional rents from holding a charity auction. Instead, bidders' surplus is greater in charity auctions if $\alpha > 0$.

5 Nonparametric Identification of Demand

The identification of the primitives of the model, $\{F(v), \alpha, \beta\}$ is necessary to assess Charitystars's objectives. Take the following example: two identical auctions with different fractions donated are observed. A mere comparison of prices across auctions could lead to incorrect conclusions on bidders' preferences. For instance, if the prices in the two auctions are close despite one auction is much more generous than the other, we may infer that bidders are not altruistic. Instead, high-value bidders could be shading their bids in the auction with the higher fraction donated due to significant externalities (Proposition 1). As a result, wrongly concluding that consumers are not altruistic has obvious repercussions on the optimal strategy of the auctioneer.

In this section, I first show identification in second-price charity auctions and then extend the analysis to Charitystars's auctions.

Second-Price Auctions. Identification relies on variation in the fraction donated (q) across otherwise identical auctions to exploit the information in the first-order conditions of optimal bidding and the monotonicity of the bid function. In what follows, denote the observed distribution of bids by $G(b(v; \alpha, \beta, q); q)$, and the related inverse hazard rate by $\lambda_G(b(v; \alpha, \beta, q); q)$.¹¹ Since the bids are invertible functions of private values, the distribution of bids is equal to the distribution of private values.¹² I use the last equivalence to write the FOC of a bidder with value v bidding $b(v; \alpha, \beta, q)$ as

$$v = (1 - \beta \cdot q) \cdot b(v; \alpha, \beta, q) + \alpha \cdot q \cdot \left(b(v; \alpha, \beta, q) - \lambda_G(b(v; \alpha, \beta, q); q) \right). \quad (5.1)$$

The equation shows that the private value must balance one's bid plus the surplus that can be extracted if somebody else wins with a larger bid.

The unknowns are v on the left-hand side and α and β on the right-hand side. Despite $F(v)$ is identified directly from the empirical distribution of bids ($\hat{G}(b)$), one can plug different combinations of $\{\alpha, \beta\}$ in equation 5.1 and obtain the same $F(v)$. A similar non-identification result holds in the estimation of risk aversion in first-price auctions. There, identification relies on either parametric quantile restrictions or variation in the number of bidders across auctions (e.g., [Lu and Perrigne, 2008](#), [Guerre et al., 2009](#), [Campo et al., 2011](#)). However, these restrictions are of no use for nonparametric identification in English

¹¹The inverse hazard rate of the bid distribution is $\lambda_G(b(v; \alpha, \beta, q); q) = \frac{1 - G(b(v; \alpha, \beta, q); q)}{g(b(v; \alpha, \beta, q); q)}$, while the inverse hazard rate of the distribution of private values is $\lambda_F(v) = \frac{1 - F(v)}{f(v)}$.

¹²Under Assumption 1 the following relations hold: $G(B) = Pr(b(v) < B) \equiv Pr(v < b^{-1}(B)) = F(b^{-1}(B))$. Therefore, $G(b(v; \alpha, \beta, q); q) = F(v)$. It follows that $g(b(v))b'(v) = f(v)$.

charity auctions as, for instance, the number of bidders does not even appear in the FOCs.

Inspecting equation 5.1, the right-hand side is strictly increasing and differentiable in $b(v; \alpha, \beta, q)$, implying that no two different combinations of α and β yield the same vector of pseudo-private values v .¹³ This remark ensures that every distribution $F(\cdot | \tilde{\alpha}, \tilde{\beta}, q)$ (one for each $\tilde{\alpha}, \tilde{\beta}$ combination given q) is unique by Theorem 1 in [Guerre et al. \(2000\)](#).¹⁴ Therefore, if two sets of auctions, A and B, with different fraction donated, $q_A \neq q_B$, are observed, the distribution of private values computed on each set of auctions using equation 5.1 must be the the same at the true parameters $\{\alpha_0, \beta_0\}$. Thus, $\{\alpha, \beta\}$ are nonparametrically identified by $F(\cdot; \alpha_0, \beta_0, q_A) = F(\cdot; \alpha_0, \beta_0, q_B)$. Once α and β are identified, $F(v)$ is identified from equation 5.1.

However, this strategy fails if a bidder's consumption value, v , depends on q – e.g., if high valued bidders systematically join auctions with greater fractions donated. Thus, the following assumption is necessary for identification:

Assumption 2. *Identification: $F(\cdot)$ does not depend on q .*

The theoretical model in Section 4 automatically satisfies this assumption because it defines $F(v)$ as the unconditional distribution of private values. Section 3 also finds that Charitystars's bidders join multiple auctions without regard for q . Also, the same section shows no correlation between the number of bidders, other auction characteristics, and q . Finally, I formally test (and do not reject) the validity of Assumption 2 in Section 6.2.

Charitystars's Auctions. To extend the previous result to Charitystars' auction, it is important to consider that not all bidders bid according to equation 4.2 in online auctions. First, the equivalence between English auctions and button auctions does not hold for those bidders who place a low bid once, and then forget to update their bids. Second, in equilibrium, the winner pays a small increment over the price at which the second-highest bidder quits bidding, suggesting that not even the winning bidder bids according to equation 4.2.¹⁵ Therefore, $G(b; q) \neq F(v)$ in online auctions, so that the unknown $F(v)$ in equation 5.1 cannot be replaced with the empirical $\hat{G}(b; q)$ to solve the problem as in the second-price auction case.

However, the winning bid is the price at which the second-highest bidder drops out, and thus, the second-highest bidder solves 5.1 at this price. As a result, the distribution of the winning bid, $G_w(b; q)$, is equal to the distribution of the second-highest bid, which

¹³The term in parentheses of equation 5.1 is increasing in b if $f'(v) > -\frac{f(v)^2}{1-F(v)} + g(b; \cdot) b''(v; \cdot)$, which is always true because of Assumption 1. This is also confirmed in the data.

¹⁴Theorem 1 in [Guerre et al. \(2000\)](#) relies on the same regularity conditions in Assumption 1.

¹⁵The minimum increment across Charitystars auctions is €1 for most auctions.

is a known function of the number of bidders and it is invertible in $F(v)$. Therefore, the counterfactual $\hat{G}(b; q)$ for a parallel second-price auction is directly identified from the empirical distribution of the winning bids and the number of bidders, which, in turn, allows the identification of α and β as in the second-price auction case above.

Proposition 2. *Under Assumptions 1 and 2, $\{F(v), \alpha, \beta\}$ are nonparametrically identified by observing two identical auctions with different fractions donated.*

Proof. See Appendix A.4.

Proposition 2 can also be extended to include a finite number of auction types (e.g., $q \in \{q_1, q_2, \dots, q_K\}$), as shown in Corollary 1 in Appendix A.5. The proof uses the panel structure of the data to create a projection matrix that cancels out the left-hand side of equation 5.1 to identify α and β as in Proposition 2.

6 Estimation of the Demand Model

In this section, I first lay out the estimation routine, which closely follows the identification in Proposition 2. Section 6.2 reports the results and fit of the model, and Section 6.3 quantifies the charity premium.

6.1 Structural Estimation

Following the main identification result, the primitives of the model $\{F(v), \alpha, \beta\}$ are estimated comparing two auctions with different fraction donated, q . Clearly, identification fails if the two fractions donated are dangerously close to each other as the necessary rank condition would not hold.¹⁶ According to Figure 1, the most frequent fraction donated in Charitystars’s data are 10%, 78% and 85%. Thus, estimation is performed on a sample of auctions with $q \in \{10\%, 85\%\}$.

Estimation is performed in three steps. The first step accounts for auction heterogeneity. In the second step, I determine the distribution of bids and construct the FOCs. The primitives are estimated in the third step of the routine.

First Step. I account for auction heterogeneity through a flexible regression of the log of transaction prices on auctions, item and charity characteristics according to the following

¹⁶Appendix Table F1 reports Monte Carlo simulations showing that the estimated $\{\hat{\alpha}, \hat{\beta}\}$ are not consistent if q^A is too close to q^B .

regression of the transaction price on covariates

$$\log(\text{price}_t) = \gamma_0 + \mathbf{x}_t \gamma + b_{w,t}, \quad (6.1)$$

where t indexes the auctions and \mathbf{x} includes all the variables in column 1 in Table 1, excluding q . The residual, $\hat{b}_{w,t}$, are interpreted as pseudo-winning bids from homogeneous auctions (e.g., Haile *et al.*, 2003), and are a function of α, β, q and winners' private values.

Appendix Table C9 reports the estimates from equation 6.1. These estimates controls for both observed and unobserved heterogeneity. In particular, the *number of bids placed* (given the *number of bidders* and the *length* of the auction) tells the level of competition across bidders within an auction that is not explained by \mathbf{x} . If the auction is more appealing for some unobservable characteristics, bidders are likely to control the auctions more closely than predicted by \mathbf{x} . The increased supervision will result in more bids by the same bidders, and as a result, will account for unobserved quality.

Second Step. The distribution and density of bids are necessary to write equation 5.1. Following the identification, I first group $\hat{b}_{w,t}$ based on q (either 10% or 85%) and determine the distribution of bids, $\hat{G}^q(b)$, from the empirical distribution of the winning bid, $\hat{G}_w^q(b)$, for each group. The densities $\hat{g}^q(b)$ are computed analogously.¹⁷ To compute the empirical CDF and pdf of $\hat{b}_{w,t}$, I use a Gaussian kernel with bandwidths as in Li *et al.* (2002).¹⁸

Third Step. I build the two sets of FOCs as in equation 5.1 based on q . I match each FOC for the auctions with $q = 10\%$ with a FOC of the auctions with $q = 85\%$ along the quantiles of the distributions of bids, i.e. FOCs with bids $b^{10\%}$ and $b^{85\%}$ are matched if $\hat{G}(b^{10\%}; q = 10\%) = \hat{G}(b^{85\%}; q = 85\%)$. In this way the left-hand side, \hat{v}^q , for each FOC is equal to its matched counterpart at the true $\{\alpha_0, \beta_0\}$, implying that at each τ quantile of the distribution of values $v_\tau^{10\%}(\alpha_0, \beta_0) - \hat{v}_\tau^{85\%}(\alpha_0, \beta_0) = 0$. Thus, the criterion function is

$$\min_{\{\alpha, \beta\}} \frac{1}{T} \sum_{\tau}^T (v_\tau^{10\%}(\alpha, \beta) - v_\tau^{85\%}(\alpha, \beta))^2, \quad (6.2)$$

where T is the number of auctions with $q = 10\%$, under the constraint that $\{\alpha, \beta\}$ are in $[0, 1]$. The distribution of private values $F(v)$ is found as the empirical distribution of the

¹⁷The distribution of bids $\hat{G}^q(b)$ is the solution to $\hat{G}_w^q(b) = n\hat{G}^q(b)^{n-1} - (n-1)\hat{G}^q(b)^n$, while its density $\hat{g}^q(b)$ solves $\hat{g}_w^q(b) = n(n-1)\hat{G}^q(b)^{n-2}[1 - \hat{G}^q(b)]\hat{g}^q(b)$, where $\hat{g}_w^q(b)$ is the empirical pdf computed on $\hat{b}_{w,t}$.

¹⁸The bandwidth of the kernel estimators are $h_g^q = c^q \cdot T_q^{-1/5}$ for pdfs and $h_G^q = c^q \cdot T_q^{-1/4}$ for CDFs. $c^q = 1.06 \cdot \min\{\sigma^q, \text{IQR}^q / 1.349\}$, T_q is the number of auctions, σ^q is the standard deviation and IQR^q is the interquartile range of $\hat{b}_{w,t}^q$ for auctions with fraction donated q . I trim the data to deal with bias at the extreme of $\hat{b}_{w,t}$ supports.

left-hand side of equation 5.1, after plugging in the estimated $\{\hat{\alpha}, \hat{\beta}\}$.¹⁹

6.2 Estimation Results

Table 3 reports the results of the estimation. The identification requires a constant number of potential bidders to perform the inversion in the second step. To avoid outliers, I set the potential number of bidders at the 99th-quantile of the distribution of bidders (first row of the table), and report estimates for various values of n . The 95% confidence interval are also reported in square brackets and are obtained by bootstrap. The estimates hardly vary with the number of potential bidders and are always significant. Consistent with other studies (e.g., DellaVigna *et al.*, 2012, Huck *et al.*, 2015), the results provide evidence for warm glow agents as $\beta > \alpha > 0$ (see Section 4). Next, I provide evidence that the model fits the data well.

Expected Revenues. I first examine simulated prices. To recover the expected price in an auction with n bidders, I plug the estimated primitives $\{F(v), \alpha, \beta\}$ in the bid equation 4.2 and integrate it with respect to the density of the second-highest bid. In all the following analyses, I compute values in euros by summing back the median values of the covariates in equation 6.1 ($x_t \gamma$) to the expected price and exponentiating it.²⁰

The differences between the observed prices across auctions with $q = 10\%$ and $q = 85\%$ are not statistically different from the expected average prices at the median number of bidders. In particular, the model predicts the expected price to be €388.73 when $q = 85\%$ while the average observed price when $q = 85\%$ and $n = 7$ is €375.50, a 3.5% deviation (p-value: 0.613). Similarly, the model predicted expected price when $q = 10\%$ and $n = 7$ is €353.87, whereas the average price in the data is €327.44, a 8.1% deviation (p-value: 0.516). The model also adequately predicts prices for other numbers of bidders as shown in Appendix Figure D5, where I vary the number of bidders between 5 and 10, which corresponds to the interquartile range of the number of bidders.

Test to Identification. The estimation procedure relies on Assumption 2, which states that $F(v)$ does not depend on q . A direct test to this assumption is to apply the estimated coefficients in the first step and the estimated $\hat{\alpha}$ and $\hat{\beta}$ to a set of auctions with $q \notin \{10\%, 85\%\}$. The identification strategy fails if the implied distribution of values differs from the estimated $\hat{F}(v)$.

¹⁹Appendix F performs a number of MonteCarlo simulations suggesting that the estimator is consistent and asymptotically normal.

²⁰I exclude the number of bidders from x because it is already accounted for in the computation of the winning bid.

I apply this procedure to the auctions with $q = 78\%$. Figure 3 compares this counterfactual density of private values (dotted line) with the estimated densities from the auctions at 10% (solid line). The two pdfs have similar shapes and the Kolmogorov-Smirnov test does not reject the null hypothesis of equality at 0.187 level. This test is rather conservative because the auction heterogeneity could impact prices when $q = 78\%$ differently compared to the case when $q \in \{10\%, 85\%\}$.

Over-Identification Test. To investigate whether bidders have different altruistic parameters, I perform a simple over-identification test in Appendix Figure D6a. I group the moments in equation 6.2 based on whether they refer to quantiles above or below the median, and estimate α and β for each sample. The plot compares the densities implied by the two sets of altruistic parameters. The null hypothesis that the two pdfs are the same cannot be rejected, meaning that the assumption of equal α and β in the population of bidders is not rejected by the data.

Collectors. Appendix Figure D4 shows that the pseudo-winning bid of collectors (as defined in Section 2) from equation 6.1 is not statistically different from that of non-collectors, further corroborating the assumption of symmetric bidding with respect to the distribution of private values.

Instrumental Variables. As in Section 3, I correct for potential endogeneity in the reserve price using instrumental variables. In particular, following the discussion in Section 3, I instrument a listing's reserve price with the average reserve price and the average number of bids placed across all the other auctions ending within five days of the auction. Appendix Table C10 shows little change both in the estimated α and β . The F-test is 33.269, and the over-identification test statistics (Sargan test) has a p-value of 0.192.

Linearity of Bids. Section 2 shows a linear relation between log prices and fractions donated. Appendix Figure D6b replicates this result by plotting the simulated log bids (y axis) for different fraction donated (x axis) (cf. Appendix Table C1 and Figure D3). I do not reject the linearity of the bid curves with respect to q via ANOVA, indicating that the model adequately reproduces the descriptive results described in Section 3.

6.3 Is There a Charity Premium?

The existence of a charity premium is debated in the literature on charity-linked goods as, for instance, some online sellers with low reputations donate to charities to look more reputable (Elfenbein *et al.*, 2012). I leverage on the structural model to cleanly estimate the charity premium and extend the counterfactual analysis to address whether donations

increase cashflows to Charitystars.

Charity Premium. Appendix Figure D7 shows that the distribution of bids (dotted line) stochastically dominates that of private values (solid line). Therefore, the expected transaction price is larger than the second-highest private value. The charity markup (dashed line, right axis) appears in Figure 4a as the percentage difference between the second-highest bid in charity auctions (solid line) over the second-highest private value (dotted line) for different fraction donated. Although the markup increases with q it is capped at 15%. This value is close to the estimates in Elfenbein and McManus (2010) of a 12% premium when the auctioneer donates 100% from eBay's Giving Works data. On the other hand, although Elfenbein *et al.* (2012) find that eBay bidders leave a 6% markup for a 10% donation, I find almost no charity premium when the auctioneer donates little. Therefore, Charitystars's demand is inelastic despite consumers' willingness to pay increases in q .

Revenue Maximizing q . Figure 4b confirms that the estimated elasticity of demand to the fraction donated (solid line) is extremely rigid. Proposition 1 states that the revenue-maximizing fraction donated is found at the intersection of the elasticity curve and the $q/(1 - q)$ curve (dotted line). The two curves intersect at $q = 0$: net revenues are beyond € 300 when the firm does not donate, and constantly decrease as q grows (dashed line, right axis). Charitystars can increase its net revenues by as much as € 250 on average by holding standard auctions.

Discussion. Despite the charity premium, the price increase does not compensate for the amount donated. Although I look exclusively at soccer jerseys, the results could be relevant for charity-linked products more broadly because of the salience and ease of measurement of Charitystars's social responsibility. Consider the case of Product Red, a charity fighting HIV in Africa whose fundraising comes from partnering with large corporations – e.g., Apple – which donate a portion of their revenues for specific goods. For instance, Montblanc Product Red trolleys currently sell for \$865, of which \$5 go to Product Red. The fact that donations are generally smaller than 10% of the price on this website shows that consumers' willingness to pay does not react substantially to firms' donations also in other markets.²¹

Consumers also face different incentives in an auction compared to the posted price environment from the example above, where anyone can buy and donate. Gneezy *et al.* (2010) investigate the willingness to pay for a photograph right after riding a roller coaster-like

²¹Similarly, Tom Shoes, a shoe company which used to donate a pair of shoes for each pair sold, has recently reverted to a much more flexible \$1 donation for every \$3 it makes as the old one-for-one donation scheme was too expensive. Source: https://media01.toms.com/static/www/images/landingpages/TOMS_Impact/TOMS_2019_Global_Impact_Report.pdf, page 69.

attraction in a US amusement park. The authors compare two strategies: posted price and pay-as-you-want plus a 50% donation. Their findings confirm my results: profits-per-ride net of donations are non-statistically different between treatment and control groups.

In conclusion, the analysis suggests that demand is unlikely to drive firms' prosocial investments. To address why Charitystars donates, the next section explores how donations impact marginal costs and profits.

7 Procurement Costs and the Profit Optimal Donation

Charitystars may find it profitable to donate if procurement costs are decreasing in the fraction donated. In this section, I first report empirical evidence of bargaining between Charitystars and the providers (mainly celebrities and charities). Conversations with advisors of the firm also confirmed this. Leveraging on this knowledge, I then turn to the cost of procuring the item and the profit-optimal donation.

Evidence of Bargainig. I first provide empirical evidence of bargaining. I exploit a period of the year where the relevant bargaining power is tilted toward the providers. The leading European soccer leagues are off in the inactive summer months of July and August, and, as objects become scarce, item providers should be more powerful. The data indicate that the average fraction donated in the summer months is significantly larger than in the remaining months (Welch tests: $\bar{q}^{August} = 0.775$, $\bar{q}^{other} = 0.698$, with a one-sided p-value = 0.030, and $\bar{q}^{July\&August} = 0.770$, $\bar{q}^{other} = 0.693$, with a one-sided p-value < 0.001). To control for other variables, I run the following OLS regressions

$$q_t = \gamma_0 + \mathbf{x}_t \gamma + \gamma_m \text{summer month}_t + \varepsilon_t, \quad (7.1)$$

where *summer month* refers to either August or to both July and August. Table 4 reports the results, confirming the presence of bargaining between parties, as Charitystars is more generous when it has less bargaining power. The results are robust to the inclusion of more covariates (even columns).

However, Charitystars could donate more to stimulate more bidders to join the auction in these summer months, where the soccer leagues are inactive (though Table 2 suggests a null effect of changes in q on the extensive margin). To solve this potential endogeneity concern, I use a similar instrumental variable approach to that in Section 2. I instrument the reserve price and the number of bidders with the mean of these variables for auctions happening within five days of each auctions. Appendix Table C4 shows that the coefficients

of the IV regressions are very similar to the OLS regressions. The F-statistic indicates a sufficiently strong first-stage (though the F-statistic is slightly below 10 in column 4), and the hypothesis of weak IV is rejected in all columns. I also perform the Sargan test of over-identification by including the average number of displayed pictures across concurrent auctions and do not reject the null.

Estimation of Procurement Costs. Let us turn to the optimal decision of a profit-maximizing charitable auctioneers, who must select the fraction donated to maximize profits, knowing that costs vary with how much is donated. Given knowledge of the number of bidders, α, β and $F(v)$, the problem of the auctioneer is

$$q^* = \arg \max_{q \in [0,1]} \int_v (1-q)b(v, \alpha, \beta, q) dF_{(n)}^{(2)}(v) - c(q),$$

where $F_{(n)}^{(2)}(v)$ is the distribution of the second highest private value out of the n bidders. Denoting the expected price by p^e and its elasticity to the donation by η , it yields

$$c'(q) = \frac{1-q}{q} \eta p^e - p^e. \quad (7.2)$$

The optimal donation equates a change in costs due to a marginal increase in q with the relative change in net revenues. In Appendix A.6, I extend the monopolist problem above to allow for bargaining over the fraction donated between the firm and the provider of the item within the framework of Nash bargaining. The model's first-order conditions can be rewritten to yields an equation similar to equation 7.2 showing that, under the mild condition that the net expected price is larger than the costs to the auctioneer, costs are strictly decreasing in q . Comparing the net revenue-maximizing donation from Proposition 1, q_R , and the profit optimal donation, q^* , implies that $q^* > q_R$ if $c'(q) < 0$. From Figure 4b, $q^R = 0$, and if also $c'(\cdot) < 0$, Charitystars optimal choice is to set $q^* > 0$. This derivation shows the importance of the cost channel on the profitability of social responsibility programs (Hart and Zingales, 2017).

To avoid losses, Charitystars ensures that the smallest net revenue from a sale covers costs. Thus, the firm sets the reserve price such that $(1-q) \cdot \text{reserve price} = c(q)$. I exploit this key information provided by the firm and estimate the average marginal costs across auctions as follows. First, I homogenize the reserve prices by regressing them on the same covariates previously used in the first step of the estimation procedure

$$\log(\text{reserve price}_t) = \mathbf{x}_t \gamma + \varepsilon_t, \quad (7.3)$$

where t indexes each one of the 1,109 auctions in the dataset (including all auctions such that $q \leq 0.85$). Second, I exponentiate the sum of the median fitted reserve price ($\widehat{\text{reserve price}}_t$) and the error terms ($\hat{\varepsilon}_t$), so that the homogenized reserve price (r_t) is expressed in terms of the median auction in euro (as in Section 6.3).²² Third, costs are equal to the net homogenized reserve price, $c_t = (1 - q)r_t$. Hence, I obtain marginal costs by regressing c_t on q using a polynomial expansion for q (i.e., $\sum_{j=0}^J \pi_j q^j$ where j is the order of each polynomial).

Including the *number of total bids placed* is helpful to account for unobservable heterogeneity in equation 7.3. In particular, if in some auctions the firm sets the reserve price above costs to limit entry in the auction to high-value bidders because some unobservable attributes of the item make it particularly appealing, the increased competition in the auction (given the *number of bidders* and *length* of the auction) will be reflected in the number of bids placed by the same bidders.

Table 5 displays the estimated coefficients using either a quadratic or a cubic functional form for costs. Comparing the two columns, the estimated intercept (π_0) and linear coefficient (π_1) are similar, while the introduction of the cubic term (π_3) inflates the size of the quadratic coefficient (π_2) in the second column. Although the coefficients are similar across columns, adding the cubic term inflates the standard errors in column 2. This effect is due to the small number of auctions for q in the neighborhood of 50%.²³ Nevertheless, both specifications seem to fit the data reasonably well as they explain a large portion of the variance of the net reserve price.

The Profit-Maximizing Fraction Donated. Figure 5a plots marginal costs and marginal net revenues. The plots show two main results. First, there is an interior solution for q^* and thus, donating maximizes profits. Despite negative marginal revenues, donations are profitable because the estimated marginal costs are also negative across both specifications for all q , implying that costs decrease in the fraction donated. The cost gains follow the law of decreasing returns because a marginal increase in q lowers costs less when q is large. Second, even accounting for costs, large donations cannot be justified: q^* is only 25% (95% C.I. [0.03, 0.37]).²⁴ By setting the donation optimally, Charitystars would substantially increase its profits per unit sold. The median amount pocketed by Charitystars is only 15% for each object sold, yielding an expectation of about €40 of profit for each auction. Figure 5b shows that profits would jump to €125 for the median auction under the optimal policy.

²²To test the impact of auction heterogeneity on q^* , I replicate the analysis in Appendix E where I consider the 1st and 3rd quartiles of auction heterogeneity ($x_t \gamma$) instead of the median auction.

²³The lack of observations in q 's middle range is due to a simple heuristic approach to bargaining: providers either get a large fraction donated and a small upfront payment and vice-versa.

²⁴Bootstrapped confidence intervals with 401 repetitions.

Behaving optimally across all auctions would more than double the firms' profits.

Discussion. The finding of decreasing costs in social responsibility could apply to other firms too. For example, [Shapira and Zingales \(2017\)](#) show that DuPont's management in the 1980s could decrease the probability of a billion-dollar fine for polluting by taking socially responsible actions.²⁵ Lessons from the supply-side analysis can be applied more generally, as they prove the importance of synergies between social responsibility programs and a firm cost structure to get corporate social responsibility to create utility for shareholders ([Hart and Zingales, 2017](#)).

8 Social Responsibility as an Objective of the Firm

The demand and supply analyses find that Charitystars correctly donates to charities, but that it donates too much. The data suggests that the optimal fraction donated is 25% on average, while the firm average donation is 70%. Next, I rule out several potential explanations and exploit a change in the capital structure of the firm to argue that Charitystars also has social motives beyond profitability.

Omitted Variables. The reserve price and the fraction donated are equilibrium outcomes: unobserved variables influencing the choice of reserve prices and fractions donated could lead to misleading conclusions. For instance, the cost estimates may not be reliable if the firm were to systematically set higher reserve prices for items with specific characteristics that I do not observe.

To account for unobservables, I instrument the reserve price in the demand model with the average reserve price and the average number of bids placed in concurrent auctions (± 5 days) as done in Section 3. I instrument the fraction donated in the supply model with the average fraction donated and the average number of bids placed. Appendix E provides a complete discussion of the IV approach, including test results. Counterfactual analysis from this model confirms that the optimal fraction donated is 0.33 and that the firm could substantially increase profits (Appendix Figure E3).

I also present similar results in Appendix E by adding more covariates to both demand and supply analyses (Appendix Figure E1) and by considering different levels of auction heterogeneity other than the median auction (Appendix Figure E4).

Reputation and Item Providers. A strategy that could reconcile Charitystars behavior

²⁵For instance, a parallel can be drawn with concrete production, which accounts for 5-7% of greenhouse emissions globally. The diffusion of technologies capable of capturing CO₂ emissions from concrete production and infusing it back in the concrete as a substitute for a portion of cement help curbing both emissions and production costs (e.g., [Hasanbeigi et al., 2012](#)).

plans to use the high-fraction donated auctions to gain reputation and build a more extensive bidder base while making profits on low-fraction donated auctions.²⁶ According to this hypothesis, a greater q improves reputation. Because a profit-maximizing firm cares for reputation if it increases profits, large fraction donated make sense as long as the number of bidders and the number of auctions grow in q .

Yet, Section 3 has already shown a limited role for the extensive margin. To provide more evidence against this hypothesis, I gathered an additional dataset of the same Charitystars's auctions over a longer horizon (extending to the end of 2018), which allows me to test whether the average fraction donated in a given week correlates with the number of bidders or the number of auctions respectively. Using different lags, Appendix Table C12 finds that the fraction donated in a week has no impact on either the average, the median, or the 8th decile of the distribution of the number of bidders in coming weeks. The same result holds for the number of auctions (Appendix Table C11).²⁷

In addition, if this mechanism were in place, we would also expect to observe a separating equilibrium based on the type of item provider, with certain providers bunching at low q and others bunching at high q based on their different bargaining powers. However, this is not true in the data. For instance, the standard deviation of the fraction donated in the aggregate data is 0.27, and it is 0.26 for items provided directly by charities, showing that the variation in q in the whole sample is similar to that for charities only.

I further study the optimal fraction donated for the auctions with known item provider in Appendix E (672 auctions). Among these auctions, I observe whether the item is provided by a charity directly (472 auctions) or by footballers and coaches. Appendix E2 confirms that even further subsetting the data, the firm optimal average donation is only 30% of the transaction price.²⁸

Competition. Charitystars is a de facto monopolist in the e-commerce of footballers' belongings because of the large number and variety of auctions it offers.²⁹ There are also considerable barriers to entry in Charitystars's business due to the need for a sizable

²⁶In principle, auctions with modest fractions donated are not necessarily more profitable because the firm sustains more significant costs to acquire these items. Yet, even under the assumption that the auctions at 85% had a different status so that they would cost zero to Charitystars, profits would still be double if the firm were to set the fraction donated at 25% compared to what it currently does.

²⁷These results also hold with monthly, instead of weekly level data, as well as with different deciles of the distribution of the number of bids.

²⁸Although it would be interesting to perform this analysis for each charity, it is not feasible because I only observe a few auctions per each charity. A potential explanation for the variation in q is that small charities could be more risk adverse, making them favour low fraction donated and higher fixed fees.

²⁹A potential competitor of Charitystars is Charitybuzz. However Charitybuzz mainly operates in US and it is not present in Europe, which is Charitystars's main market (see Appendix Table C5 for a breakdown of top bidders by nationality). Besides Charitybuzz does not offer charity auctions of soccer jerseys.

network of contacts with celebrities, and a large number of users.

Wrong Beliefs. Although the firm could fail to properly assess the elasticity of prices to the fraction donated, this explanation is rather unlikely because the firm hosts thousands of auctions yearly. The firm has sufficient data to realize that prices do not substantially covary with the fraction donated and can also experiment with different auctions.

Multiple Purchases. Charitystars's large donations could be optimal to stir users to other areas of the business, such as selling a painting, or a dinner with a CEO. Yet, conversations with advisors of the firm reveal that most users in the dataset have a particular interest in soccer jerseys, and that bidders do not bid across multiple item categories. In addition, since they are scattered around the world, there are large transaction costs in bidding for certain items such as exclusive event, like a dinner with a celebrity.

Managerial Costs. Soccer jerseys are the most active area of Charitystars's business, and Charitystars's managers should probably give them priority over other areas of the business (DellaVigna and Gentzkow, 2019). The managerial team remained constant in the period under study.

Evidence for Social Objectives. I argue that the firm's objectives also include the social impact achieved through hefty donations. To support this conclusion, I provide empirical evidence that the firm adjusted its strategy after a change in its equity structure.

In April 2017, a set of additional investors invested in Charitystars by purchasing an undisclosed equity share. The new investors included a venture capital fund. The entry did not affect the management of the company, nor the CEO. The CEO is also the funder as well as one of the principal shareholders. I study how the entry affected the donations. In particular, the average fraction donated is 75.1% until May 2017, but it drops to 45.9% (one-sided p-value < 0.1%) from June 2017 until November 2018, when my data end, providing first evidence that the firm's strategy has shifted after the entry.

Appendix Table C13 performs a similar analysis by regressing the fraction donated on a dummy variable that is one after the entry. These regressions also account for several covariates, including month and year fixed effects. To control for the item provider, I also add charity fixed effects in columns 3 and 6. As in Section 3, I control for potential unobservable heterogeneity in two ways. First, all columns include the number of bids placed, which captures quality characteristics affecting bargaining over q that are observed by bidders. Second, I implement an instrumental variable approach analogous to that in Section 3 to account for endogeneity in the reserve price variable in columns 4-6. I instrument a listing's reserve price with the average reserve price in the other auctions ending within a five days window. The instrument is not valid if, for instance, providers

systematically strikes multiple deals with Charitystars at the same time. However, the fixed effects control such (uncommon) event. Overall, the results are robust across columns and indicate that the firm donated considerably less after the entry of the fund.³⁰

Due to the drop in q , average net revenues increased substantially from €128.13 to €244.68 (one-sided p-value < 0.1%) after the entry. Despite the drop in q , the lower donations did not decrease the number of auctions. Instead, the average number of auctions in a week increased from 14.1 to 17.5 after the entry (one-sided p-value = 2.07%), while the number of bidders staid fairly constant (p-value: 0.6148).³¹

Discussion. The decrease in the fraction donated is connected to the entry of a fund in Charitystars's equity. The fund gains by steering the company towards higher profitability to quickly reselling it. The generous donations in the pre-entry period did not depend on the inflexibility of the provider of the item to agree on better terms with Charitystars. The post-entry data shows that Charitystars can still find items even by donating less, and therefore the large donations are to be seen as a choice of Charitystars. These arguments point to Charitystars's objectives also embodying social purpose.

The steady growth of corporate social responsibility programs across both large and small businesses calls into question whether the sole purpose of these activities is to foster profits. Understanding why firms engage in social responsibility is a necessary intermediate step to address whether social responsibility creates values for shareholders. If the returns to social responsibility are inverted U-shaped as for Charitystars, comparing firms at the two extremes of some index of social responsibility as is customary in the applied literature may not provide meaningful results. Failing to understand why firms engage in socially responsible programs could be the root cause of some contradicting results in the literature (e.g., [Margolis et al., 2007](#), [Eccles et al., 2014](#), [Ferrell et al., 2016](#)).

Today, several firms, including large multinationals like Danone, are turning their subsidiaries into benefit corporations. These firms are a type of for-profit social impact companies whose legal goal is the best interest of the corporation while respecting their employees, community, and environment (e.g., [Battilana and Lee, 2014](#)). In particular, this legal status keeps managers of socially responsible firms accountable not only for their

³⁰Appendix Table C14 runs similar OLS regressions for different deciles of the weekly fraction donated on a dummy variable that is one after the entry. These OLS regressions also account for the average number of weekly bidders and the average fraction donated in the previous week, as well as month and year fixed effects. The estimates indicate that after the entry, the distribution of the fraction donated shifted towards left by sharply reducing the number of auctions where the firm donates considerably.

³¹Appendix Table C15 shows the estimates from poisson and IV regressions of the number of bidders on covariates. The reserve price is instrumented with the average reserve price and the avera number of pictures displayed on each listing across concurrent auctions as in previous analyses. The results show a statistically significant, but economically negligible drop in the number of bidderes after the entry.

company's financial performance but also for their social performance. 35 U.S. states and the District of Columbia now legally recognize benefit corporations, and legislators across Europe are in the process of approving laws promoting social impact firms. Understanding the objective of these firms and their market conduct is, therefore, an important economic question for economically informed policy-making.

9 Conclusions

What is the broader purpose of a firm? I provide evidence that a firm's objective can extend beyond profit maximization to include also social responsibility. The analysis focuses on a socially-responsible for-profit firm that offers auctions of celebrities' belongings. To purchase memorabilia that will be consequently auctioned on the company's online platform, the firm bargains with item providers – mainly charities and celebrities. The two parties also decide what fraction of the transaction price is donated back to the charity after the auction. Consumers know beforehand the fraction that will be donated. I show that social responsibility – i.e., the donations – impact both revenues and costs, and compare actual donations with the profit-maximizing benchmark. The results from a structural model of demand and supply indicate that the firm could increase its profits substantially by behaving optimally. I exploit a change in the equity structure of the firm to connect this result to the firm's prosocial inclinations. The analysis also indicates that consumers' willingness to pay minimally responds to giving, even though donations are especially salient in this environment. Therefore, demand is not a likely driver of firms' investments in social responsibility.

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Tables and Figures

Table 1: Relation between the transaction price and fraction donated

Transaction price	(I)	(II)	(III)	(IV)
Fraction donated (q)	87.147*** (15.261)	84.083*** (15.555)	85.604*** (16.534)	94.227*** (17.226)
Reserve price	0.823*** (0.037)	0.825*** (0.037)	0.819*** (0.040)	0.812*** (0.041)
Number of bidders	4.966*** (1.705)	5.081*** (1.717)	4.476*** (1.710)	4.127** (1.719)
Main variables	Y	Y	Y	Y
Add. charity dummies		Y	Y	Y
League/match dummies			Y	Y
Time dummies				Y
Adjusted R-squared	0.567	0.568	0.581	0.592
BIC	14,049	14,065	14,135	14,211
N	1,109	1,108	1,108	1,108

Note: OLS regression of log of the transaction price on covariates. Control variables are defined in Appendix B. Robust standard errors in parenthesis.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table 2: Relation between the rate of daily bidders and percentage donated

Number of daily bidders	(I)	(II)	(III)	(IV)
Fraction donated (q)	0.032 (0.055)	0.050 (0.057)	-0.000 (0.059)	0.029 (0.058)
Main variables	Y	Y	Y	Y
Add. charity dummies		Y	Y	Y
League/match dummies			Y	Y
Time dummies				Y
Pseudo R-squared	0.125	0.127	0.139	0.151
N	1,108	1,108	1,108	1,108

Note: Poisson regression of the number of bidders on covariates. The length of the auction is used as exposure variable. Control variables are defined in Appendix B. Robust standard errors in parenthesis.
 $*$ - $p < 0.1$; $**$ - $p < 0.05$; $***$ - $p < 0.01$.

Table 3: Estimated altruistic demand parameters

Number of bidders		α	β
Quantile	n	[95% CI]	[95% CI]
99%	16	17.4% [7.6%, 26.8%]	42.7% [23.2% 57.7%]
95%	14	17.2% [7.5%, 25.2%]	42.7% [18.7% 56.1%]
90%	12	16.9% [7.3%, 25.5%]	42.7% [20.7% 57.6%]
75%	10	16.5% [6.8%, 25.7%]	42.6% [21.4% 60.3%]
50%	7	15.5% [6.0%, 23.5%]	42.4% [19.8% 57.5%]

Note: The table displays results from the structural estimation of α and β for selected quantiles of the distribution of the number of bidders. The preference parameters α and β represent the additional utility due to somebody else's donations or due to the bidder's own donation, respectively. Refer to equation 4.1 in Section 4 for more information. The 95% confidence intervals are reported in square brackets. The CI are found by bootstrap with replacement (401 times). Dataset restricted to all auctions such that $q \in \{10\%, 85\%\}$. 730 observations in total.

Table 4: Evidence of bargaining

Fraction donated (q)	(I)	(II)	(III)	(IV)
August	0.070** (0.029)	0.074** (0.030)		
July & August			0.077*** (0.022)	0.068*** (0.024)
Main variables	Y	Y	Y	Y
Add. charity dummies		Y		Y
League/match dummies		Y		Y
Adjusted R-squared	0.311	0.354	0.316	0.357
N	1,109	1,109	1,109	1,109

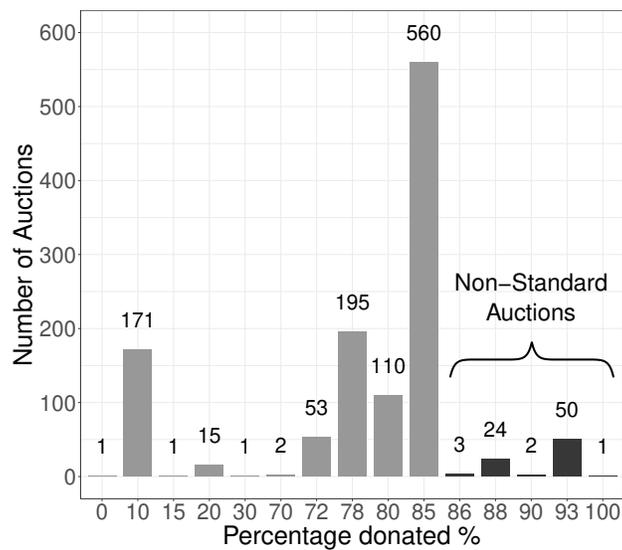
Note: The table displays estimates from OLS regressions of the fraction donated on covariates. The top panel shows the coefficients of the dummy variables August (1 if the month is August, 0 otherwise) and July and August (1 if the month is either July or August, 0 otherwise) as in equation (7.1) Control variables are defined in Appendix B. Robust standard errors in parentheses.
* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table 5: Cost estimation

Costs:	(I) Quadratic	(II) Cubic
π_0 (constant term)	236.60*** (15.18)	250.26*** (94.31)
π_1 (linear term)	-428.99*** (82.58)	-596.09 (1101.82)
π_2 (quadratic term)	211.92*** (81.22)	578.10 (2326.45)
π_3 (cubic term)		-222.24 (1365.89)
Adjusted R-squared	0.591	0.582
BIC	11,926	11,973
N	1,108	1,108

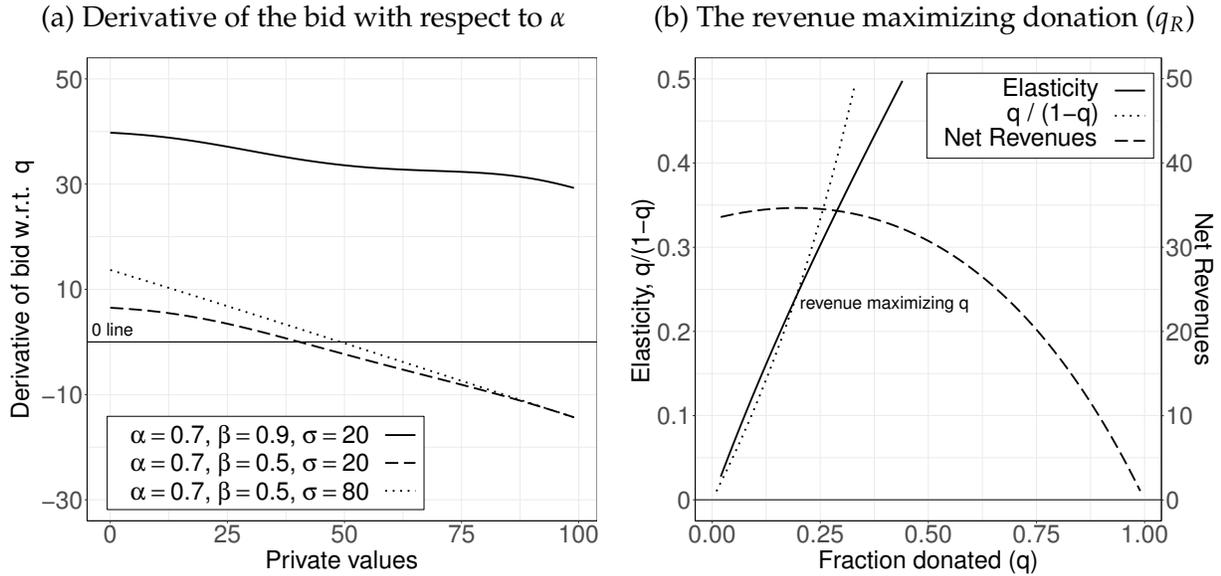
Note: The table displays estimates from OLS regressions of the recovered procurement cost on a quadratic (Column I) and a cubic (Column II) polynomial expansion of q . π_0 is the intercept, while π_1, π_2 and π_3 refers to the linear (q), quadratic (q^2) and cubic term (q^3). Robust standard errors in parentheses.
* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Figure 1: Number of auctions by percentage donated



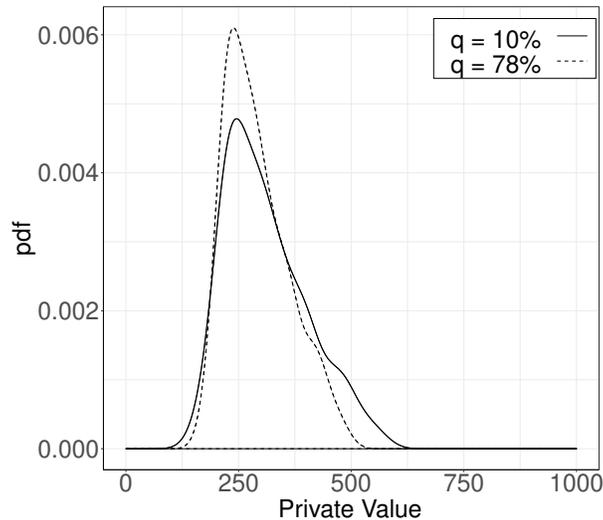
Note: The barplot displays the number of auctions available in the dataset by percentage donated. The plot includes only auctions of items for a price in (€100, €1,000) with reserve price was greater than 0, at least two bidders and minimum increment not greater than €25. There are 1,189 auctions in total. Charitystars generally withholds at least 15% of the final price and therefore all auctions whose percentage donated is above 85% are excluded from the analyses as these are special one-off charitable events (black columns). However, non-standard auctions are also counted in when computing variables such as those accounting for the number of auctions hold for the same player or for the same team in the past two and three weeks respectively.

Figure 2: The impact of a change in q on bids and revenues



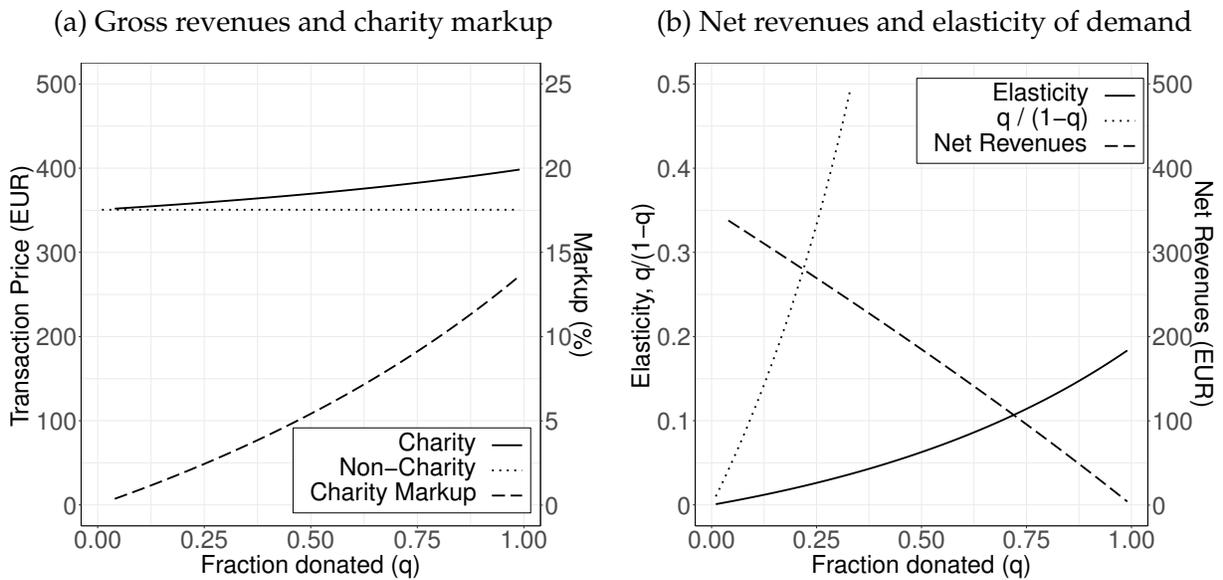
Note: Panel a. The figure reports the analytical derivative of the bid function equation 4.2 w.r.t. q . $q = 85\%$ and $F(\cdot)$ is a truncated normal in $[0, 100]$ with mean 50 and standard deviation σ . Panel b. The figure shows the optimal percentage donated (q_R) obtained at the intersection of the elasticity of the expected winning bid with respect to q and the curve $q/(1-q)$. Values of the elasticity and $q/(1-q)$ (solid and dotted curves) are on the left vertical axis. The right axis shows the net revenues (dashed curve) (or second-highest bid times $(1-q)$): $(1-q) \int_0^1 b(v) dF_{(n)}^{(2)}(v)$. The distribution of values $F(v)$ is uniform on $[0, 100]$, $\alpha = 0.5$, $\beta = 0.7$ and there are two bidders.

Figure 3: Out-of-sample validation



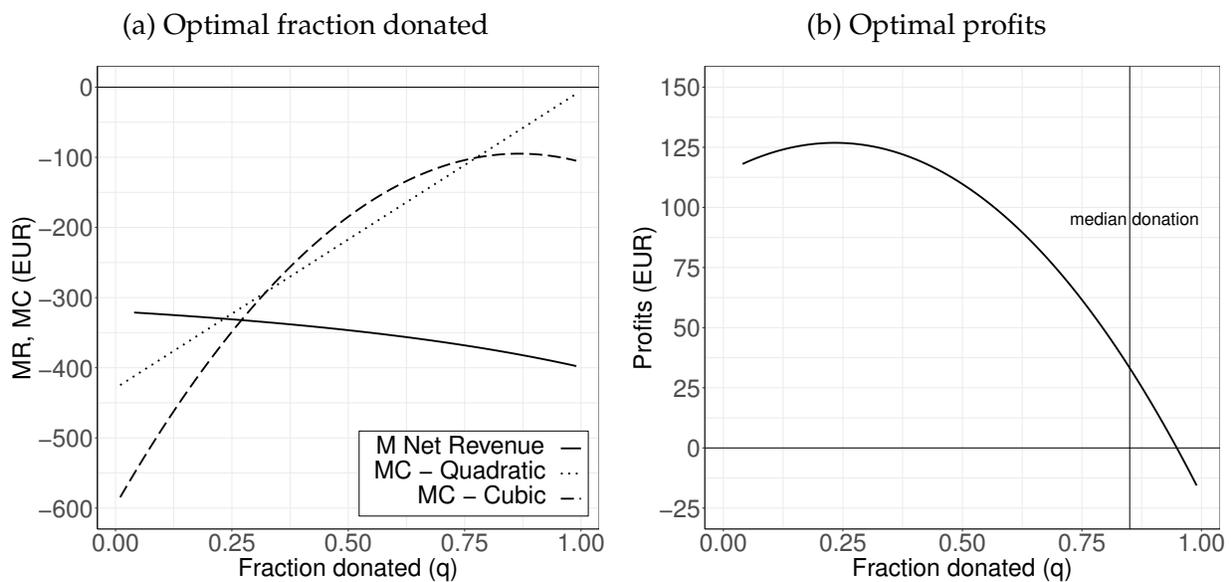
Note: The plot compares the density of the private values estimated from the structural model employing data from auctions with $q = \{10\%, 85\%\}$ and the density of the private values obtained projecting the three-step estimation procedure on the $q = 78\%$ auctions. The null hypothesis (equality) cannot be rejected at standard level (p-value: 0.1874). The estimations assume $n = 16$, a Gaussian kernel and Silverman's rule-of-thumb bandwidth (Silverman, 1986). The density $f(v)$ is approximated using a cubic spline.

Figure 4: Charity premium



Note: Panel a. The plot displays the expected gross revenues to Charitystars at the estimated primitives (solid line), the revenues from a similar second-price non-charity auction (dotted line), and the charity markup (dashed line, right axis). Panel b. The plot displays the expected net revenues (dashed line, right axis), the elasticity of the winning bid (solid line, left axis) and the ratio $q/(1-q)$ (dotted line, left axis) for varying levels of q . The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Revenues assume that the number of potential bidders is 7 in both plots.

Figure 5: Optimal donation



Note: Panel a. The plot displays the optimal fraction donated as the intersection of marginal costs (dotted and dashed lines) and net benefits (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) and cubic polynomials (dashed line). Panel b. The plot displays how profits change with the fraction donated (q). The vertical line at 85% indicate the median donation by Charitystars. The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Profits are computed as net revenues minus costs as in the quadratic polynomials case. Marginal revenues assume that the number of potential bidders is 7 in both plots.

Online Appendix

A Theoretical Appendix

A.1 Lemma A1

This lemma show conditions for $b(v) = v$ when $\alpha \geq \beta$ and $b(v) = v/(1 - q\beta)$ when $\alpha < \beta$. These results are necessary to prove Lemma 1.

Lemma A1. *Assume that $\alpha \geq \beta$. The bid function $b(v)$ crosses the 45° line only once if $b(\underline{v}) \geq \underline{v}$, and either never or two times if $b(\underline{v}) < \underline{v}$.*

Proof: *Case 1: $b(\underline{v}) \geq \underline{v}$.* The bid function evaluated at the upper bound, $b(\bar{v}) = \frac{\bar{v}}{1+q\alpha-q\beta}$ implies that $b(\bar{v}) < \bar{v}$.¹ Thus, given this, one need to show that there exists only one \hat{v} such that $b(\hat{v}) \leq \hat{v} \forall v \in [\underline{v}, \hat{v}]$ and $b(\hat{v}) < \hat{v}$, then $b(v) < v \forall v \in (\hat{v}, \bar{v}]$.

The following condition holds at $b(v) = v$

$$(\alpha - \beta)q = \frac{1}{v} \int_v^{\bar{v}} \left(\frac{1 - F(x)}{1 - F(v)} \right)^{\frac{1-q\beta}{q\alpha} + 1} dx,$$

which is obtained substituting $b(v) = v$ in the left-hand side of equation 4.2. Multiplying both sides of the equation by $(1/q\alpha) \cdot f(v)/[1 - F(v)]$ gives

$$\frac{1}{q\alpha} \frac{f(v)}{1 - F(v)} (\alpha - \beta)q = \frac{1}{v} \frac{\partial b(v)}{\partial v}, \quad (\text{A.1})$$

where the right-hand side includes the derivative of the bidding function w.r.t. v , which is positive because

$$\frac{\partial b^*(v; \alpha, \beta, q)}{\partial v} = \begin{cases} \frac{1}{q\alpha} \int_v^{\bar{v}} \left(\frac{1 - F(x)}{1 - F(v)} \right)^{\frac{1-q\beta}{q\alpha} + 1} dx \frac{f(v)}{1 - F(v)} > 0, & \text{if } \alpha > 0 \wedge q > 0 \\ \frac{1}{1 - q\beta} > 0, & \text{if } \alpha = 0 \vee q = 0. \end{cases} \quad (\text{A.2})$$

Assume that there are three values $v_1 < v_2 < v_3$ such that the bid computed at each value is equal to the value itself. Given that $b(v)$ is differentiable and $b(v) \neq v$ for $v \notin \{v_1, v_2, v_3\}$, it must be that $b(v) < v$ for $v \in (v_1, v_2)$ and $v \in (v_3, \bar{v}]$ and $b(v) > v$ for $v \in (\underline{v}, v_1)$ and $v \in (v_2, v_3)$. The increasing hazard rate property gives

$$\begin{aligned} \frac{1}{q\alpha} \frac{f(v_2)}{1 - F(v_2)} (\alpha - \beta)q &> \frac{1}{q\alpha} \frac{f(v_1)}{1 - F(v_1)} (\alpha - \beta)q, \\ \frac{1}{q\alpha} \frac{f(v_3)}{1 - F(v_3)} (\alpha - \beta)q &> \frac{1}{q\alpha} \frac{f(v_2)}{1 - F(v_2)} (\alpha - \beta)q. \end{aligned}$$

¹This result is obtained by applying L'Hospital's rule to $\int_v^{\bar{v}} \left(\frac{1 - F(x)}{1 - F(v)} \right)^{\frac{1-q\beta}{q\alpha} + 1} dx$ and because of the increasing hazard rate assumption.

Because equation A.1 must hold at v_1, v_2 and v_3 , it implies that

$$\frac{\frac{\partial b(v_2)}{\partial v_2}}{\frac{\partial b(v_1)}{\partial v_1}} > \frac{v_2}{v_1} > 1 \quad \text{and} \quad \frac{\frac{\partial b(v_3)}{\partial v_3}}{\frac{\partial b(v_2)}{\partial v_2}} > \frac{v_3}{v_2} > 1,$$

a contradiction. While the ratio of the derivative at v_2 and v_1 must be larger than 1, as the curve intersects the 45° line from below the line, this cannot happen at v_3 and v_2 , because the intersection happens from above the line. The bid function crosses the 45° line at v_2 from below, while it crosses the same line from above at v_3 , implying

$$\frac{\partial b(v_3)}{\partial v_3} < \frac{\partial b(v_2)}{\partial v_2}.$$

Figure A1b provides a graphical representation. Because v_1, v_2 and v_3 are arbitrary values, the proof holds for all v . Given that $b(v) \geq v$, $b(\bar{v}) < \bar{v}$ and because $b(v)$ cannot cross the 45° line more than twice without violating the increasing hazard rate property, it must be that $b(v) = v$ at most once.

Case 2: $b(v) < v$. This case follows immediately from the previous derivation, given that $b(v)$ cannot cross the 45° line more than twice without violating the increasing hazard rate assumption. This implies that $b(v) = v$ for either two values v_1 and v_2 or no value at all. In this case, in order to respect the increasing hazard rate property, the bid function meets the diagonal line from below at the first cutoff and from above at the second cutoff, making a cutoff like v_3 infeasible. ■

A.2 Proof of Lemma 1

Bids are

- increasing in q if $\beta \geq \alpha$;
- decreasing in q in the interval $(\tilde{v}, \bar{v}]$, where $\tilde{v} \in [v, \bar{v}]$, if $\alpha > \beta$.

Proof: Assume $q > 0$ and let $\tilde{\alpha} = q \cdot \alpha$ and $\tilde{\beta} = q \cdot \beta$. First we analyze the derivative of $b(v)$ w.r.t. q when $\alpha = 0$, which is:

$$\frac{\partial b^*(v; \alpha = 0, \beta, q)}{\partial q} = \frac{\beta v}{(1 - \tilde{\beta})^2} > 0.$$

The derivative in this case is always positive as $\beta < 1$ and $q < 1$, meaning that bids increase in q .

Turn now to the derivative with respect to q when α is positive. This proof has multiple steps. (*step 1*) I establish that for $\beta \geq \alpha > 0$ the bid is increasing in $q \forall v$. (*step 2*) I focus on the remaining case ($\beta < \alpha$) and show that the derivative of the bid w.r.t. q can have both positive and negative values. (*step 2.a*) I show that, at the value such that the derivative is zero (called \tilde{v}), if the bid is larger than the value the derivative of $b(v)$ w.r.t. q is decreasing. (*step 2.b*) In the final step, I show conditions for the uniqueness of \tilde{v} .

Step 1: $\beta \geq \alpha > 0$. The derivative of equation 4.2 w.r.t. q for $\alpha > 0$ is

$$\frac{\partial b^*(v; \alpha > 0, \beta, q)}{\partial q} = \frac{\int_v^{\bar{v}} \left(\frac{1-F(x)}{1-F(v)} \right)^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}} \left(-\frac{\alpha(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}^2} \log \frac{1-F(x)}{1-F(v)} - (\alpha - \beta) \right) dx - (\alpha - \beta)v}{(1 + \tilde{\alpha} - \tilde{\beta})^2}. \quad (\text{A.3})$$

An application of the L'Hospital's Rule shows that the integral is continuous and finite everywhere with respect to x . Inspection of this equation reveals that is positive if $\beta \geq \alpha$. Therefore, bids are

increasing in q if $\beta > \alpha$ for all v .

Step 2: $0 < \alpha < \beta$. Under this configuration, equation A.3 crosses the x-axis at \tilde{v} s.t. $\frac{\partial b(v)}{\partial q} \Big|_{v=\tilde{v}} = 0$. Rewriting equation A.3 and evaluating it at \tilde{v} yields

$$\begin{aligned} - \int_v^{\bar{v}} \left(\frac{1-F(x)}{1-F(v)} \right)^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}} \frac{\alpha(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}^2} \log \frac{1-F(x)}{1-F(v)} dx &= (\alpha - \beta) \left(v + \int_v^{\bar{v}} \left(\frac{1-F(x)}{1-F(v)} \right)^{\frac{1-\tilde{\beta}}{\tilde{\alpha}}+1} dx \right) \Big|_{v=\tilde{v}} \\ &= (\alpha - \beta)(1 + \tilde{\alpha} - \tilde{\beta})b(\tilde{v}). \end{aligned} \quad (\text{A.4})$$

where the second line replaces the expression to the right-hand side with the optimal bid function in equation 4.2. Thus, equation A.3 can be either positive or negative.

Step 2.a. This step shows that equation A.3 is decreasing at \tilde{v} if $b(\tilde{v}) \geq \tilde{v}$. Given that the right-hand side of equation A.4 is increasing in v everywhere, it will also be increasing in v at \tilde{v} . To show that there is at most one \tilde{v} , it suffices to show that the left-hand side is a decreasing function of v , at \tilde{v} . The derivative of the left-hand side w.r.t. v is

$$- \int_{\tilde{v}}^{\bar{v}} \left(\frac{1-F(x)}{1-F(\tilde{v})} \right)^{\frac{1-\tilde{\beta}}{\tilde{\alpha}}+1} \alpha \frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}^2} \left(1 + \frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}} \log \frac{1-F(x)}{1-F(\tilde{v})} \right) dx \frac{f(\tilde{v})}{1-F(\tilde{v})}, \quad (\text{A.5})$$

while the derivative of the right-hand side can be rewritten as

$$\frac{(\alpha - \beta)(1 + \tilde{\alpha} - \tilde{\beta})}{\tilde{\alpha}} \frac{(b(\tilde{v})(1 + \tilde{\alpha} - \tilde{\beta}) - \tilde{v}) f(\tilde{v})}{1 - F(\tilde{v})}. \quad (\text{A.6})$$

Putting together equation A.5 and equation A.6 and using equation A.4 to rewrite equation A.5 in terms of bids and values, equation A.3 is decreasing at \tilde{v} if

$$\begin{aligned} - (b(\tilde{v})(1 + \tilde{\alpha} - \tilde{\beta}) - \tilde{v}) \alpha \frac{1 + \tilde{\alpha} - \tilde{\beta}}{\tilde{\alpha}^2} + (\alpha - \beta) \frac{(1 + \tilde{\alpha} - \tilde{\beta})^2}{\tilde{\alpha}} b(\tilde{v}) \\ \leq \frac{(\alpha - \beta)(1 + \tilde{\alpha} - \tilde{\beta})}{\tilde{\alpha}} (b(\tilde{v})(1 + \tilde{\alpha} - \tilde{\beta}) - \tilde{v}) \\ \Rightarrow b(\tilde{v}) \geq \tilde{v}. \end{aligned}$$

This means that equation A.3 is positive at the left of \tilde{v} and negative to the right of \tilde{v} . Therefore, as long as the equilibrium bid at the cut-off value \tilde{v} is greater than the cut-off itself, bids will be decreasing in q for all $v > \tilde{v}$, if $\alpha > \beta$.

Step 2.b. When $\alpha > \beta$, the limit of equation A.3 for $v \rightarrow \bar{v}$ is negative. In fact, under the increasing hazard rate condition (Assumption 1) applying L'Hospital's rule to the first term (in the numerator) of equation A.3 yields

$$\lim_{v \rightarrow \bar{v}} \frac{\int_v^{\bar{v}} (1-F(x))^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}} \left(-\frac{\alpha(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}^2} \log \frac{1-F(x)}{1-F(v)} - (\alpha - \beta) \right) dx}{(1 + \tilde{\alpha} - \tilde{\beta})^2 (1 - F(v))^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}}} = 0,$$

while the limit of the remaining part is $\lim_{v \rightarrow \bar{v}} -(\alpha - \beta)v = -(\alpha - \beta)\bar{v} < 0$. There are two cases: in Case 1 \tilde{v} is unique and in Case 2 either \tilde{v} does not exist or there are two \tilde{v} .

Step 2.b: Case 1. The first case assumes $b(\underline{v}) \geq \underline{v}$. To show that \tilde{v} is unique I merge two results: (i)

the limit of equation A.3 is negative at the upper bound of the support of v , and (ii) there is no region on the support of v such that $b(v) < v$ inside the region and $b(v) > v$ outside the region. Therefore, equation A.3 cannot switch sign from negative to positive and back to negative again, implying that if \tilde{v} exists, it is unique.

Recall from Lemma A1 that when $b(\underline{v}) \geq \underline{v}$, $b(v)$ intersects the 45° line only once at, say, \tilde{v} such that $b(v) > v$ for $v < \tilde{v}$ and $b(v) < v$ for $v > \tilde{v}$. The result in step 2.a coupled with the requirements (i) that equation A.3 is negative when evaluated at the upper bound, (ii) that equation A.3 is continuous on the support of v , and (iii) Lemma A1, necessarily means that equation A.3 cannot switch sign more than once. Therefore, $\tilde{v} < \bar{v}$ as otherwise $\partial b(v)/\partial q|_{v=\bar{v}} > 0$. In fact, equation A.3 is increasing at \tilde{v} for $\tilde{v} \geq \bar{v}$, which implies that equation A.3 is positive for $v > \tilde{v}$. Then, equation A.3 must switch sign again to negative in order to satisfy the $\partial b(v)/\partial q|_{v=\bar{v}} < 0$ condition, but this is not possible in this region because of \tilde{v} is unique and $b(v) < v$ for $v > \tilde{v} \geq \bar{v}$. (see Figure A1a).

In addition, the uniqueness of \tilde{v} implies that \tilde{v} does not exist if equation A.3 is negative at \underline{v} . In this case, the derivative of the bid w.r.t q will always be negative. Therefore, if \tilde{v} exists, it is unique and separates those who increase their bid (low value bidders) from those who decrease it (high-value bidders).

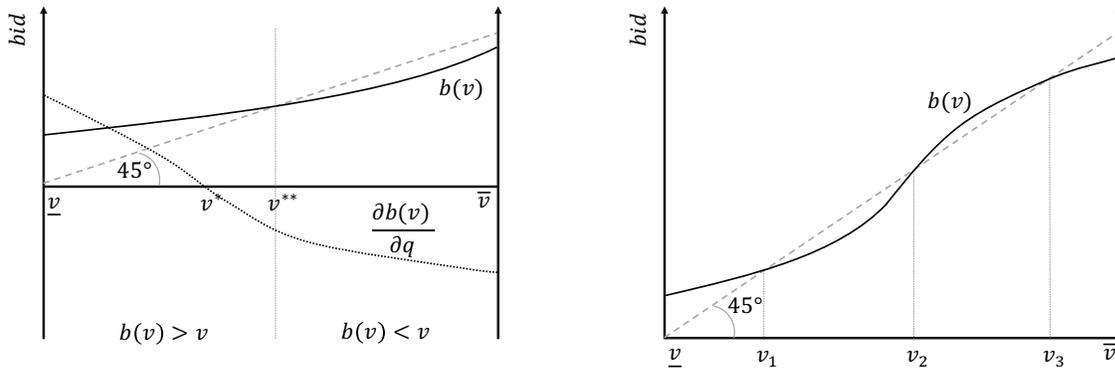
Step 2.b: Case 2. The second case assumes $b(\underline{v}) < \underline{v}$. Lemma A1 proves that there are either no \tilde{v} or that there are exactly two \tilde{v} so that the bid function cuts the 45° line twice. It follows that there exist either no cutoff or exactly two $\tilde{v} = \{\tilde{v}_1, \tilde{v}_2\}$ such that equation A.3 is increasing at \tilde{v}_1 and decreasing at \tilde{v}_2 , with $\tilde{v}_1 < \tilde{v}_2$ because the limit of equation A.3 is negative at the upper bound. In fact, it must be that $b(\tilde{v}_1) < \tilde{v}_1$ and $b(\tilde{v}_2) > \tilde{v}_2$.

Hence, when $\alpha > \beta$ there exists a value \tilde{v} such that (at least some) bidders with values below \tilde{v} increase their bids, while all bidders with values above \tilde{v} decrease it after a marginal increase in q . When instead $\alpha \leq \beta$ all bidders increase their bids after a marginal increase in q . ■

Figure A1: Illustration of the proofs of Lemma 1 and Lemma A1

(a) Lemma 1

(b) Lemma A1



Note: Panel (a) shows the effect of a marginal increase in q when $\alpha > \beta$ assuming that $b(\underline{v}) > \underline{v}$. The complementary case would show two \tilde{v} , such that the derivative (dotted line) is negative for the lowest value bidders, positive for the bidders with values between \tilde{v}_1 and \tilde{v}_2 and negative for the highest value bidders. Panel (b) shows that the bid is steeper at v_2 than at v_3 . Lemma A1 states that if $b(v)$ oscillates around the 45° line it violates the increasing hazard rate assumption.

A.3 Proof of Proposition 1

Define $\eta(p^e, q) = \frac{\partial p^e}{\partial q} \frac{q}{p^e}$ as the elasticity of the expected price, p^e , to the donation, q . When $\alpha = 0$, the auctioneer should not donate. When $\alpha > 0$, the revenue maximizing donation solves $\eta(p^e(q_R), q_R) = \frac{q_R}{1 - q_R}$.

Proof: The auctioneer's expected revenues can be written as:

$$\mathbb{E}[R(\alpha, \beta, F(v); q)] = \begin{cases} \int_{\underline{v}}^{\bar{v}} (1 - q) \cdot \frac{1}{1 + q \cdot (\alpha - \beta)} \left\{ v + \int_v^{\bar{v}} \left(\frac{1 - F(x)}{1 - F(v)} \right)^{\frac{1 - q \cdot \beta}{q \cdot \alpha} + 1} dx \right\} dF_{(n)}^{(2)}(v), & \text{if } \alpha > 0 \text{ and } q > 0 \\ \int_{\underline{v}}^{\bar{v}} (1 - q) \cdot \frac{v}{1 - q \cdot \beta} dF_{(n)}^{(2)}(v), & \text{if } \alpha = 0 \text{ or } q = 0. \end{cases}$$

Assuming $q > 0$, there are two cases depending on whether $\alpha = 0$ or $\alpha > 0$.

Case 1: $\alpha = 0$. The derivative of the expected revenues w.r.t. q is negative as $\beta \in (0, 1)$. Therefore, the auctioneer is always better off by setting $q = 0$.

Case 2: $\alpha > 0$. To simplify the notation, given α and β , denote the bid of a bidder with valuation v in an auction where \tilde{q} is donated by $b(v, \tilde{q})$. The expected net revenue in a second-price charity auction is

$$\int_{\underline{v}}^{\bar{v}} (1 - q) b(v, q) dF_{(n)}^{(2)}(v).$$

Denote the expected price by $p^e = \int_{\underline{v}}^{\bar{v}} b(v, q) dF_{(n)}^{(2)}(v)$ and let η be the elasticity of the expected price to a marginal change in q : $\eta = \frac{\partial \ln p^e}{\partial \ln q} = \frac{\partial p^e}{\partial q} \frac{q}{p^e}$. By the dominated convergence theorem, the derivative of the expected price with respect to q can be rewritten as $\frac{\partial p^e}{\partial q} = \int_{\underline{v}}^{\bar{v}} \frac{\partial b(v, q)}{\partial q} dF_{(n)}^{(2)}(v)$. Using the elasticity formula, $\int_{\underline{v}}^{\bar{v}} \frac{\partial b(v, q)}{\partial q} dF_{(n)}^{(2)}(v) = \eta \frac{p^e}{q}$.

The optimal fraction donated is the q that solves the FOCs of the auctioneer's problem (the second-order conditions are satisfied):

$$\int_{\underline{v}}^{\bar{v}} -b(v, q) + (1 - q) \frac{\partial b(v, q)}{\partial q} dF_{(n)}^{(2)}(v) = 0.$$

Substituting ηp^e for the derivative of the bid, the optimal q is given by $\eta = \frac{q}{1 - q}$. ■

A.4 Proof of Proposition 2

Under Assumptions 1 and 2, $\{F(v), \alpha, \beta\}$ are nonparametrically identified by observing two identical auctions with different fractions donated.

Proof: Assume first that all bids are observed as in a second-price auction. To simplify the notation I denote a bid only by $b(v)$ and the bid distribution, density and hazard by $G(b)$, $g(b)$ and $\lambda_G(b)$, respectively. The researcher observes two types of auction, A and B, and the only difference among them is the fraction of the transaction price that will be donated, i.e. $q^A \neq q^B$.

Because the distribution of values $F(\cdot)$ is the same across auctions A and B by Assumption 2, then for each value corresponding to the τ -quantile of the value distribution, v^x , the distribution of bids computed at that τ -quantile must be equal, i.e. $G(b^x | q^A) = G(b^x | q^B)$. Therefore, after rewriting the first order condition for each set of auctions as in equation 5.1 I can match the FOCs from the two auctions based on the quantiles of the bid distribution. This gives the following equation for

each quantile of v^x :

$$v_x^A - v_x^B = b_x^A - b_x^B + (\alpha - \beta) \cdot (q^A \cdot b_x^A - q^B \cdot b_x^B) - \alpha \cdot (q^A \cdot \lambda_G(b_x^A) - q^B \cdot \lambda_G(b_x^B)), \quad (\text{A.7})$$

where $G(b^x) = G(b_x^A) = G(b_x^B)$. Since $v_x^A - v_x^B = 0$, eq. A.7 can be rewritten in matrix notation as

$$\Delta(b_x) = \mathbf{B}_x \times \begin{bmatrix} \alpha - \beta \\ -\alpha \end{bmatrix}, \quad (\text{A.8})$$

where $\Delta(b_x) = -(b_x^A - b_x^B)$ and \mathbf{B}_x is the matrix $[q^A b_x^A - q^B b_x^B; q^A \cdot \lambda_G(b_x^A) - q^B \cdot \lambda_G(b_x^B)]$.

The matrix \mathbf{B}_x has full rank because the two columns are linearly independent. To prove this assume to the converse that \mathbf{B}_x is not invertible and therefore that its columns are linearly dependent (i.e. $b_x = k \cdot \lambda_G(b_x)$ for both auctions A and B). It follows that $G(b_x) = 1 - b_x \cdot g(b_x)/k$ for a constant $k > 0$. Note that k must be positive because otherwise $G(b_x) > 1$ as $g(b_x) \geq 0, \forall b_x$. The previous differential equation admits a solution $g(b_x) = c \cdot (b_x)^{-(k+1)}$, where c is an integration constant. Thus, $G(b_x) = 1 - c \cdot (b_x)^{-k}/k$. Evaluating the CDF at $b_x = 0$ yields $G(0) = -\infty, \forall k > 0$. Moreover, the inverse hazard rate

$$\lambda_G(b_x) = \frac{1 - 1 + c \cdot (b_x)^{-k}/k}{c \cdot (b_x)^{-(k+1)}} = \frac{b_x}{k} \quad \text{for } k > 0,$$

is increasing in b_x . This implies that

$$\frac{1 - F(v_x)}{f(v_x)} = \frac{1 - G(b(v_x))}{g(b(v_x)) \cdot b'(v_x)} = \frac{1}{k} \frac{b(v_x)}{b'(v_x)},$$

which is an increasing function because (i) the optimal bidding function $b(v)$ is increasing in the private value v_x and (ii) the bidding function $b(v_x)$ maximizes a bidder's utility ($b''(v_x) \leq 0$). This means that the inverse hazard rate is not decreasing and that therefore $b(v_x)$ is not a best response for v_x . This is a contradiction, which proves that the columns in \mathbf{B}_x are not linearly dependent and that \mathbf{B}_x is invertible.² Given that \mathbf{B}_x has full rank, α, β and $F(v)$ are nonparametrically identified.

To extend this result to Charitystars's auctions, note that the distribution of the winning bid ($G_w(b)$) is identified from the data. In equilibrium, the distribution of the winning bid is equal to the distribution of the second-highest bid ($G_w(b) = G_{(n)}^2(b)$). Therefore, $G(b)$ is found as the root (in $[0, 1]$) of $G_w(b) - nG(b)^{n-1} + (n-1)G(b)^n$. The FOCs equation 5.1 can then be written for each $\{\alpha, \beta\}$. Therefore, one can apply the same logic shown above, and identify α, β . Finally, with knowledge of the couple $\{\alpha, \beta\}$, the distribution of private values, $F(v)$, is identified from the FOCs equation 5.1 of the winning bids. ■

A.5 Proof of Corollary 1

Corollary 1. α, β and $F(v)$ are also nonparametrically identified when the dataset includes more than 2 types of auctions.

Proof: To simplify the notation I denote a bid only by $b(v)$ and the bid distribution, density and

²If $k = 1$, then $g(b_x) = 0$ for $b_x < 0$ and $g(b_x) > 0$ for $b_x \geq 0$. Therefore $g(\cdot)$ is the Dirac delta function, which is not differentiable and does not admit a decreasing inverse hazard rate. In turn, given that $F(v) = G(b(v))$, the non-differentiability of $G(\cdot)$ implies that also the distribution of values $F(\cdot)$ is not differentiable, a contradiction.

hazard by $G(b), g(b)$ and $\lambda_G(b)$, respectively. Assume that q has dimension K_C and that K_x quantiles of the distribution of values are observed. The FOC equation 5.1 in matrix notation becomes

$$V_{K_x \times K_C} = (\alpha - \beta) \times_{K_x \times K_C} B_{K_x \times K_C} \times_{K_C \times K_C} Q^C + B_{K_x \times K_C} - \alpha \times_{K_x \times K_C} \Lambda_{K_x \times K_C} \times_{K_C \times K_C} Q^C, \quad (\text{A.9})$$

where V is a matrix of dimension $K_x \times K_C$ displaying the value v_x for the x -quantile (row) in auction of type C (column), and 0 otherwise. Similarly, Q^C is a diagonal matrix with entries equal to the percentage donated q^C and 0. The other matrices are defined as:

$$B = \begin{bmatrix} b_0^1 & b_0^2 & \dots & b_0^{K_C} \\ \vdots & \vdots & \ddots & \vdots \\ b_1^1 & b_1^2 & \dots & b_1^{K_C} \end{bmatrix}, \quad \Lambda = \begin{bmatrix} \lambda_G^1(b_0^1) & \lambda_G^2(b_0^2) & \dots & \lambda_G^{K_C}(b_0^{K_C}) \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_G^1(b_1^1) & \lambda_G^2(b_1^2) & \dots & \lambda_G^{K_C}(b_1^{K_C}) \end{bmatrix},$$

where superscripts indicate that the fraction donated is equal to q^j for $j \in [1, K_C]$ and subscripts indicate the x -quantiles of the distribution of values or bids.

There exists a projection M (with rank $K_C - 1$) such that $V \times M = 0$. Postmultiplying equation A.9 by M and moving terms, the following equation represents the FOC where the dependent variable is a known object

$$-B \times M = (\alpha - \beta) \times B \times Q^C \times M - \alpha \times \Lambda \times Q^C \times M.$$

After stacking the matrices in vectors, the last equation can be represented by the system of equations

$$y = [b \quad l] \times \begin{bmatrix} \alpha - \beta \\ -\alpha \end{bmatrix},$$

where $y = \text{vec}(-B \times M)$, $b = \text{vec}(B \times Q^C \times M)$, $l = \text{vec}(\Lambda \times Q^C \times M)$, and $\text{vec}(\cdot)$ indicates the vectorization of the matrices in parentheses.

Nonparametric identification requires showing that b and l are linearly independent, which follows directly from the argument in the proof of Proposition 2 in Appendix A.4. Hence, b and l are not linearly dependent, establishing identification of α , β and $F(v)$. ■

A.6 The Bargaining Problem

This section provides a micro foundation to the condition for the optimal q^* in equation 7.2 in Section 7. The surplus to the firm is the difference of the net revenues $(1 - q)p$ and the procurement cost κ . For simplicity, κ does not vary with q . Item providers (i.e., charities and celebrities) care for the amount that is ultimately donated. For simplicity they incur no cost in giving the item. The bargaining weights are ω for the firm and $1 - \omega$ for the provider. In this bargaining framework, q maximizes

$$((1 - q)p^e - \kappa)^\omega \cdot (qp^e + \kappa)^{1-\omega},$$

where p^e denotes the expected highest price, and is a function of the distribution of values, the charity parameters (i.e., α and β), the number of bidders and q . The first-order condition with

respect to q can be rearranged to obtain

$$-p^e \left(\frac{(1-\omega)((1-q)p^e - \kappa)}{\omega\kappa + q((1-q)p^e - \kappa)} \right) = \frac{1-q}{q} \eta p^e - p^e, \quad (\text{A.10})$$

where η is the elasticity of the expected price to a change in q . The right-hand side is the same as in equation 7.2, while the left-hand side is a function of the primitives.

The left-hand side can be interpreted as the marginal cost of the monopolist problem as in Section 7 ($c'(q)$). When $\omega = 1$, all bargaining power is in the hand of Charitystars, the left-hand side becomes 0, and the optimal q^* solves $\eta = \frac{q}{1-q}$, as in the revenue maximization case (see Proposition 1). Because there is no bargaining, setting a greater q does not yield any cost savings (i.e., $c'(q) = 0$). Since Charitystars sets the reserve price to break even, the fraction in parenthesis on the left-hand side is always positive (i.e., $(1-q)p^e > \kappa$). Therefore when $0 \leq \omega < 1$, the left-hand side is negative, implying negative marginal costs in the model in Section 7.

Finally, the left-hand side in equation A.10 can be rearranged by adding and subtracting $1/q$ in the term in parentheses

$$-p^e \left(-\frac{\omega}{q} \frac{\kappa + q((1-q)p^e - \kappa)}{\omega\kappa + q((1-q)p^e - \kappa)} + \frac{1}{q} \right) \approx -\frac{p^e}{q}(1-\omega),$$

which gives a clean interpretation of the marginal cost in terms of the bargaining weight and primitives of the model.

B Data Description

The data was collected using a Python script that searched a list of keywords across the pages dedicated to soccer items on the company website, available at <http://www.charitystars.com>. The script would gather all the available information regarding the auction, the charity, the listing and the bid history. This information was augmented with data from other sources. For example, a similar python script was used to recover footballers' quality scores from a renowned videogame (*FIFA*). Information on each charity's mission was obtained from both Charitystars as well as each charity's website.

The analysis considers only a subset of the available auctions (see Section 2), according to the following conditions: (i) transaction prices higher than the reserve price, (ii) reserve prices greater than zero, (iii) two or more bidders, (iv) minimum increment is within €25 and (v) maximum donation of 85% of the final price.

B.1 Description of the Variables

The regressions in Section 2 and in the Appendix display only some of the actual variables used in the analyses due to space limitations. These variables were distinguished in four groups based on their relevance.

1. *Main Variables*: these are the variables used in all regression tables and in the structural model. They are listed in Table B1 and their meaning is described by their label. Some variables whose meaning is not immediately clear are described in the following list:
 - The variable *Length* counts the number of days between the first bid and the closing date (the listing date of the auction is unknown).
 - The dummy *Extended time* is 1 if two or more bidders placed a bid in the last minutes of the auction. In this case the time is extended until all but 1 bidders drop out
 - *Auctions within 3 weeks (same team)* counts the number of auctions listing jerseys of the same team as the one of the auctioned item. It only includes auctions within a 3 week window from the end of the auction. It considers all auctions not only those with final price larger than €100 and smaller than €1000.
 - *Auctions up to 2 weeks ago (same player/team)* counts the number of auctions for a jersey worn by the same player playing with the same team in the same year as the match of the jersey that is auctioned. It considers all the listings up to 2 weeks from the end of the auction (Charitystars's auctions last between 1 and 2 weeks). It considers all auctions not only those with final price larger than €100 and smaller than €1000.
 - *Count auctions same charity* is a progressive count of the number of listings for each charity.
 - The dummy *Player belongs to FIFA 100 list* is 1 if the player is in the FIFA 100 list (the list of the best soccer players ever).
 - The variable *Number of goals scored* is equal to the number of goals scored by the player with the auctioned jersey in a particular match *if* this number is mentioned in the content of the listing. It is zero otherwise.
 - The dummy *Player belongs to an important team* is 1 if the player plays for one of the following teams (alphabetic order): AC Milan, Argentina, Arsenal FC, AS Roma, Atletico

de Madrid, Barcelona FC, Bayern Munich, Belgium, Borussia Dortmund, Brazil, Chelsea FC, Colombia, England, FC Internazionale, France, Germany, Italia, Juventus FC, Liverpool FC, Manchester City, Manchester United, Netherlands, PSG, Real Madrid, Sevilla FC, Spain, SS Lazio, SSC Napoli, Uruguay.³

2. *Add. Charity Dummies*: this group includes dummies for heterogeneity across charities based on the mission of each charity. These dummies are not exclusive bins as most charities do more than only one activity. There are 101 different charities in total. The dummy variables used

- *Helping disables individuals* for charities involved in assistance to disable subjects.
- *Infrastructures in developing countries* for charities building infrastructures in developing countries.
- *Healthcare* for charities dealing with healthcare and health research.
- *Humanitarian scopes in developing countries* for charities helping people in situation of poverty and undernourishment.
- *Children's wellbeing* for charities providing activities (e.g., education and sport) to the youth.
- *Neurodegenerative disorders* for charities helping those suffering from neurodegenerative disorders.
- *Charity belongs to the soccer team* are charities linked to a football team.
- *Improving access to sport* charities give opportunity of integration through sport activities.
- *Italian charity*.
- *English charity*.

3. *League/Match Dummies*: these are dummies for soccer league and match heterogeneity. They include:

- Dummies for each major competition (*Champions League, Europa League, Serie A, Italian Cup, Premier League, La Liga, Copa del Rey, European Supercup, Italian Supercup, Spanish Supercup, UEFA European Championship, Qualifications to UEFA European Championship, World Cup, Qualification to the World Cup*⁴).
- Dummies weather the listings mentions that the match was won (*Won*) and for unofficial/replica jerseys which are not worn but only signed (*Unofficial*). There are only 79 jerseys in the dataset that are replica, and they are all signed by the player.

4. *Time Dummies*: this group include *Month* dummies (12 variables) and *Year* dummies (2 variables).

³In unreported analysis player quality was accounted also using the players' evaluation from the videogame FIFA. These variables do not affect prices significantly and are dropped.

⁴All remaining competitions are treated as friendly matches.

Table B1: Summary statistics

Variable	Mean	St.Dev.	Q(25%)	Q(50%)	Q(75%)
<i>Auction characteristics</i>					
Percentage donated (q)	0.70	0.27	0.78	0.85	0.85
Transaction price in €	364.25	187.50	222.00	315.00	452.50
Reserve price in €	179.03	132.02	100.00	145.00	210.00
Minimum increment in €	1.71	3.15	1.00	1.00	1.00
Number of bidders	7.83	3.27	5.00	7.00	10.00
Number of bids placed	24.97	18.36	11.00	20.00	34.00
Sold at reserve price (b)	0.04	0.20	0.00	0.00	0.00
Length (in # days)	8.08	3.07	7.00	7.00	7.00
Extended time (b)	0.43	0.50	0.00	0.00	1.00
<i>Web-listing details</i>					
Length of description (in # words)	141.89	42.11	123.00	140.00	161.25
Content in English (b)	0.30	0.47	0.00	0.00	1.00
Content in Spanish (b)	0.00	0.07	0.00	0.00	0.00
Length of charity description (in # words)	123.47	56.62	107.00	107.00	120.00
Number of pictures	5.67	1.98	5.00	6.00	7.00
# of auctions within 3 weeks (same team)	1.46	4.08	0.00	0.00	1.00
# of auctions up to 2 weeks ago (same player/team)	5.06	7.92	0.00	1.00	7.00
Count auctions same charity	128.35	151.94	14.00	54.00	216.50
<i>Player and match characteristics</i>					
Player belongs to FIFA 100 list (b)	0.11	0.31	0.00	0.00	0.00
Unwashed jersey (b)	0.09	0.29	0.00	0.00	0.00
Jersey is signed (b)	0.52	0.50	0.00	1.00	1.00
Jersey is signed by the team players/coach (b)	0.06	0.24	0.00	0.00	0.00
Jersey worn during a final (b)	0.03	0.17	0.00	0.00	0.00
Number of goals scored	0.03	0.20	0.00	0.00	0.00
Player belongs to an important team (b)	0.88	0.32	1.00	1.00	1.00
<i>Charity provenience</i>					
Charity is Italian (b)	0.90	0.29	1.00	1.00	1.00
Charity is English (b)	0.08	0.28	0.00	0.00	0.00
<i>Charity's activity</i>					
Helping disables individuals (b)	0.35	0.48	0.00	0.00	1.00
Infrastructures in developing countries (b)	0.09	0.29	0.00	0.00	0.00
Healthcare (b)	0.23	0.42	0.00	0.00	0.00
Humanitarian scopes in developing countries (b)	0.14	0.34	0.00	0.00	0.00
Children's wellbeing (b)	0.84	0.36	1.00	1.00	1.00
Neurodegenerative disorders (b)	0.06	0.23	0.00	0.00	0.00
Charity belongs to the soccer team (b)	0.10	0.29	0.00	0.00	0.00
Improving access to sport (b)	0.63	0.48	0.00	1.00	1.00

Note: Overview of the main covariates used in all specifications in the reduced form analysis and in the structural model. Binary variables are denoted by (b). Prices are in Euro. If the listing is in GBP the final price is converted in euro using the exchange rate of the last day of auction

C Additional Tables

Table C1: Linearity of the relation between the logarithm of the transaction price and percentage donated

log(Transaction price)	(I) OLS	(II) Q(0.25)	(III) Q(0.50)	(IV) Q(0.75)
Fraction donated (q)	0.212*** (0.046)	0.228*** (0.054)	0.305*** (0.089)	0.334*** (0.079)
F-test of equality with OLS (p-value)		0.762	0.299	0.124
Main variables	Y	Y	Y	Y
Adjusted/pseudo R-squared	0.502	0.353	0.326	0.315
N	1,108	1,108	1,108	1,108

Note: The table displays estimates from OLS and quantile regressions of the logarithm of the transaction price on covariates. The null hypothesis that the coefficient of the fraction donated (q) is the same in column (II), (III) and (IV) is not rejected at 0.429 levels (F-test = 0.85). The last three columns report Pseudo R-squared in place of Adjusted R-squared. The coefficients of the quantile regressions are plotted in Appendix Figure D3. Control variables are defined in Appendix B. Robust standard errors in parenthesis.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C2: OLS and IV regressions for the transaction price.

	(I)	(II)	(III)	(IV)
Transaction price	OLS	IV	IV	IV
Fraction donated (q)	90.687*** (17.068)	141.796* (84.163)	146.408* (88.907)	182.071* (96.339)
Reserve price	0.770*** (0.042)	0.807*** (0.181)	0.834*** (0.184)	0.803*** (0.193)
Number of bidders	12.793*** (1.480)	13.319*** (1.540)	13.341*** (1.597)	12.256*** (1.617)
First-stage F-stat		11.725	11.003	10.521
Weak-instrument p-value		0.001	0.001	0.001
Main variables	Y	Y	Y	Y
Add. charity dummies	Y		Y	Y
League/match dummies	Y			Y
Adjusted R-squared	0.537	0.516	0.516	0.456
N	1,109	1,107	1,106	1,106

Note: The table displays estimates from OLS and IV regressions of the transaction price on covariates. The reserve price and the fraction donated are instrumented using the average reserve price and average fraction donated across all concurrent auctions (for each auction I take the average across all other auctions ending in the previous and successive five days to the end of the auction). The middle panel reports the Kleibergen-Paap Wald F statistic for the first-stage test and the Anderson-Rubin Wald test for the weak-instrument test. For over-identification, the Sargan test is conducted including also the mean number of bidders across concurrent auctions as an additional instrument. The test p-values for specifications analogous to columns 2, 3 and 4 are 0.847, 0.817 and 0.145 respectively. The Hausman test (not reported) does not reject the null hypothesis of exogeneity of the reserve price and q at common values. League/Match Dummies are partialled out in Column 4. Control variables are defined in Appendix B. Robust standard errors in parentheses.

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Table C3: OLS and IV regressions for the number of daily bidders.

	(I)	(II)	(III)	(IV)
Number of daily bidders	OLS	IV	IV	IV
Fraction donated (q)	0.077 (0.054)	0.030 (0.253)	0.099 (0.268)	0.045 (0.278)
First-stage F-stat		21.287	18.316	15.971
Montiel-Pflueger robust p-value		0.05	0.05	0.05
Over-id p-value		0.473	0.499	0.431
Main variables	Y	Y	Y	Y
Add. charity dummies	Y		Y	Y
League/match dummies	Y			Y
Adjusted R-squared	0.296	0.269	0.270	0.160
N	1,109	1,107	1,106	1,106

Note: The table displays estimates from OLS and IV regressions of the number of daily bidders (ratio of the Number of Bidders and Number of Days) on covariates. The fraction donated is instrumented using the average fraction donated and the average reserve price across all concurrent auctions (within ± 5 days). The table reports the Kleibergen-Paap Wald F statistic for the first-stage test and the Montiel-Pflueger robust weak instrument test. The Hausman test (not reported) does not reject the null hypothesis of exogeneity of the reserve price and q at common values. League/Match Dummies are partialled out in column 4. Control variables are defined in Appendix B. The reserve price and auction length are not included as covariates. Control variables are defined in Appendix B. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C4: Evidence of bargaining: IV regressions

	(I)	(II)	(III)	(IV)
Fraction donated (q)	(OLS)	(IV)	(OLS)	(IV)
August	0.074** (0.030)	0.107*** (0.039)		
July & August			0.068*** (0.024)	0.112*** (0.034)
First-stage F-stat		10.480		9.613
Weak-instrument p-value		0.022		0.004
Main variables	Y	Y	Y	Y
Add. charity dummies	Y	Y	Y	Y
League/match dummies	Y	Y	Y	Y
Adjusted R-squared	0.354	0.270	0.357	0.187
N	1,109	1,107	1,109	1,107

Note: The table displays estimates from OLS and IV regressions of the fraction donated on covariates. The top panel shows the coefficients of the dummy variables August (1 if the month is August, 0 otherwise) and July and August (1 if the month is either July or August, 0 otherwise) as in equation (7.1). The reserve price and the number of bidders are instrumented using the average reserve price and the number of bidders across all concurrent auctions (for each auction I take all the auctions ending in the previous and successive five days to the end of the auction). The table reports the Kleibergen-Paap Wald F statistic for the first-stage test and the Anderson-Rubin Wald test for the weak-instrument test. For over-identification (Sargan test) the average number of pictures across concurrent auctions (± 5 days) is also included as an additional instrument. The test p-value for specifications analogous to columns 2 and 4 are 0.166 and 0.221 respectively. League/Match Dummies are partialled out in columns 2 and 4. Control variables are defined in Appendix B. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C5: Nationalities of the top bidders

	Italian	UK	France	Other EU	North Am	China	Asia	East Asia	Rest World	Tot
Winner	561	74	41	119	62	130	35	28	59	1,109
	50.67%	6.67%	3.70%	9.92%	5.59%	11.72%	3.16%	2.52%	5.32%	-
Second	604	79	28	113	51	117	33	26	58	1,109
	54.46%	7.12%	2.52%	10.20%	4.60%	10.55%	2.98%	2.34%	5.23%	-
Total	1,165	153	69	232	113	247	68	54	117	-

Note: Nationalities of the top bidders by geographic area. "Rest of the World" includes also Unknown nationalities (12 winners and highest losers in total).

Table C6: Regression of the transaction price on a winning bidder's nationality

Transaction price	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Fraction Donated (q)	84.854*** (16.535)	85.274*** (16.542)	85.731*** (16.502)	85.533*** (16.549)	85.554*** (16.609)	84.798*** (16.468)	85.516*** (16.532)
Win: Italy	-6.489 (7.856)						
Win: UK		12.719 (15.581)					
Win: France			-18.343 (17.575)				
Win: European Union				1.092 (12.276)			
Win: North America					24.844 (16.210)		
Win: China						16.098 (13.007)	
Win: Asia							-19.164 (21.529)
Main variables	Y	Y	Y	Y	Y	Y	Y
Add. charity dummies	Y	Y	Y	Y	Y	Y	Y
League/match dummies	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.581	0.581	0.581	0.580	0.581	0.581	0.581
BIC	14,153	14,153	14,153	14,153	14,151	14,152	14,153
N	1,109	1,109	1,109	1,109	1,109	1109	1,109

Note: The table displays estimates from OLS and IV regressions of the transaction price on covariates including dummies for the most common nationalities of the winning bidder. Control variables are defined in Appendix B. Robust standard errors in parenthesis.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C7: Regression of the transaction price on recurrent winners

Transaction price	(I)	(II)	(III)	(IV)
Recurrent winner	10.814 (7.681)	18.163 (17.872)	10.814 (7.681)	18.163 (17.872)
Fraction donated (q)	85.575*** (15.234)	89.904*** (17.690)	85.575*** (15.234)	89.904*** (17.690)
Recurrent winner · fraction donated (q)		-10.406 (24.858)		-10.406 (24.858)
Main variables	Y	Y	Y	Y
Marginal effect		7.757 (11.504)		10.829 (11.533)
Adjusted R-squared	0.567	0.567	0.567	0.567
N	1,109	1,109	1,109	1,109

Note: The table displays estimates from OLS regressions of the transaction price on covariates including the dummy variable Recurrent Winner, which is 1 if the winner of the auction won more than 3 auctions (the median in the data). Recurrent Winner is interacted with the fraction donated in even columns. The table shows that the marginal effect of Recurrent Winner is not significantly different from zero (odd columns). Control variables are defined in Appendix B. Robust standard errors in parenthesis.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C8: Overview of the most common models of giving

Model	Overview
Noncharity ($\alpha = \beta = 0$)	Bidders do not pay a premium in charity auctions.
Pure altruism ($\alpha = \beta > 0$)	Bidders obtain extra utility from donating, and are willing to pay a premium. They do not distinguish across sources of donation.
Warm glow ($\beta > \alpha > 0$)	Bidders derive greater satisfaction from their own donation (impure altruism).
See-and-be-seen ($\beta > \alpha = 0$)	Bidders derive utility only from their own donation. Limiting case of warm glow ($\alpha = 0$).
Volunteer skill ($\alpha > \beta > 0$)	Bidders obtain greater utility from giving by others.

Note: The preference parameters α and β represent the additional utility due to somebody else's donations or due to the bidder's own donation, respectively. Refer to equation 4.1 in Section 4 for more information. Source: [Leszczyc and Rothkopf \(2010\)](#).

Table C9: First step of the structural estimation

	(I) Coefficient	(II) S.E.
log(Transaction price)		
log(Reserve price)	0.371***	(0.024)
Minimum increment	0.019	(0.014)
Minimum increment ²	0.0001	(0.0004)
log(Number of bidders)	0.036	(0.044)
Sold at reserve price (0/1)	-0.121**	(0.049)
log(Total number of bids placed)	0.261***	(0.028)
Length	0.052***	(0.018)
Length ²	-0.002***	(0.001)
Extended time (0/1)	-0.029	(0.030)
Length of description	0.001**	(0.0004)
Content in English	-0.057	(0.037)
Content in Spanish	-0.010	(0.138)
Length of charity description	-0.0003	(0.0003)
Number of pictures	-0.029	(0.022)
Number of pictures ²	0.003	(0.002)
Number of same team auctions within 3 weeks	0.010**	(0.004)
Number of same player auctions within 2 weeks	0.009***	(0.002)
Number auctions from the same charity	-0.001***	(0.0002)
Player belongs to FIFA 100 list (0/1)	0.110**	(0.047)
Unwashed jersey (0/1)	0.207***	(0.048)
Jersey is signed (0/1)	0.086**	(0.037)
Jersey is signed by the team players/coach (0/1)	0.061	(0.074)
Jersey worn during a final (0/1)	0.338***	(0.098)
Number of goals scored wearing the jersey	0.186***	(0.061)
Player belongs to an important team (0/1)	0.242***	(0.046)
Charity is English (0/1)	0.168	(0.132)
Charity is Italian (0/1)	0.208	(0.134)
Charity deals with disabilities (0/1)	0.088**	(0.039)
Charity builds infrastructures in developing countries (0/1)	0.153**	(0.069)
Charity deals in healthcare (0/1)	-0.146**	(0.057)
Charity has a humanitarian scopes in developing countries (0/1)	0.094	(0.065)
Charity deals with children's wellbeing (0/1)	0.068	(0.064)
Charity deals with neurodegenerative disorders (0/1)	0.041	(0.084)
Charity belongs to a soccer team (0/1)	-0.185**	(0.081)
Charity aims to improve access to sport (0/1)	0.010	(0.066)
Constant	2.225***	(0.249)
Adjusted R-squared	0.522	
F Statistic	23.708***	(df = 35; 694)
N	730	

Note: The table displays estimates from OLS regressions of the logarithm of the transaction price as in the first step of the structural model. (0/1) indicates dummies. Control variables are defined in Appendix B. Robust standard errors in parenthesis in column 2.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C10: Estimated altruistic demand parameters with instruments

Number of bidders		α	β
Quantile	n	[95% CI]	[95% CI]
99%	16	17.3%	43.1%
		[6.12%, 29.6%]	[18.5% 63.4%]
95%	14	17.1%	43.0%
		[8.1%, 30.6%]	[21.9% 63.9%]
90%	12	16.8%	43.0%
		[7.4%, 28.9%]	[23.6% 60.7%]
75%	10	16.4%	42.9%
		[7.3%, 28.5%]	[22.2% 60.9%]
50%	7	15.4%	42.8%
		[7.3%, 25.4%]	[24.3% 60.3%]

Note: The table displays results from the structural estimation of α and β for selected quantiles of the distribution of the number of bidders. The first step regression is replaced with a 2SLS regression, where the reserve price is instrumented with the average reserve price and the average number of bids placed in concurrent auctions (± 5 days). The F-test is 33.269, and the over-identification test statistics (Sargan test) has a p-value of 0.192. The preference parameters α and β represent the additional utility due to somebody else's donations or due to the bidder's own donation, respectively. Refer to equation 4.1 in Section 4 for more information. The 95% confidence intervals are reported in square brackets. The CI are found by bootstrap with replacement (401 times). Dataset restricted to all auctions such that $q \in \{10\%, 85\%\}$. 727 observations in total.

Table C11: The impact of the fraction donated on the number of auctions over time

Number of auctions (weekly)	(I)	(II)	(III)
Lagged number of auctions (weekly)	0.003	0.002	0.003
	(0.068)	(0.068)	(0.068)
Average q (weekly)	-5.282	-5.183	-5.544
	(5.609)	(5.713)	(5.854)
Average q (weekly) , lag 1 week		-0.526	-0.816
		(4.980)	(5.181)
Average q (weekly) , lag 2 week			1.965
			(4.960)
Adjusted R-squared	0.302	0.299	0.293
N	266	266	265

Note: The table displays estimates from OLS regressions of the weekly number of auctions. The data includes all auctions of actually worn soccer jerseys between June 19th, 2013, and November 6th, 2018 (3,968 auctions, 267 weeks in total). All regressions include a constant and month and year fixed effects. The qualitative results would not change using monthly data. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C12: The impact of the fraction donated on the number of bidders over time

	Independent Variables				Adj. R-sq.	N
	Lagged Dep. Var.	Avg. q (week)	Avg. q (lag 1)	Avg. q (lag 2)		
<i>Dependent variable: Average number of bidders (weekly)</i>						
Average num. bidders	0.289** (0.866)	1.380 (0.850)			0.559	266
Average num. bidders	0.282*** (0.055)	1.198 (0.864)	1.048 (0.759)		0.560	266
Average num. bidders	0.288*** (0.055)	1.306 (0.863)	1.136 (0.771)	-0.683 (0.769)	0.554	265
<i>Dependent variable: Median number of bidders (weekly)</i>						
Q(50%) num. bidders	0.346*** (0.062)	1.438 (0.940)			0.492	266
Q(50%) num. bidders	0.342*** (0.061)	1.334 (0.970)	0.596 (0.861)		0.491	266
Q(50%) num. bidders	0.350*** (0.062)	1.497 (0.955)	0.729 (0.865)	-1.005 (0.850)	0.486	265
<i>Dependent variable: 8th decile of the number of bidders (weekly)</i>						
Q(80%) num. bidders	0.228*** (0.059)	1.045 (1.154)			0.520	266
Q(80%) num. bidders	0.224*** (0.059)	0.721 (1.150)	1.761* (1.045)		0.522	266
Q(80%) num. bidders	0.228*** (0.059)	0.652 (1.172)	1.712 (1.059)	0.268 (1.111)	0.514	265

Note: The table displays estimates from OLS regressions of the weekly number of bidders. The dependent variable varies across rows, while the independent variables vary across columns. The lagged dependent variable is in column 1. Weekly observations. The data includes all auctions of actually worn soccer jerseys between June 19th, 2013, and November 6th, 2018 (3,968 auctions, 267 weeks in total). All regressions include a constant and month and year fixed effects. The qualitative results would not change using monthly data. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C13: Charitystars’s donations before and after the recapitalization

Fraction donated (q)	OLS			IV for Reserve price		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Post entry (0/1)	-0.098*** (0.018)	-0.082*** (0.019)	-0.064*** (0.018)	-0.095*** (0.018)	-0.080*** (0.019)	-0.063*** (0.018)
Reserve price	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000* (0.000)
First-stage F-stat				208.761	176.850	101.566
Montiel-Pflueger robust test p-value				≤ 0.05	≤ 0.05	≤ 0.05
Over-id p-value				0.333	0.274	0.331
Additional controls		Y	Y		Y	Y
Charity FEs			Y			Y
Adjusted R-squared	0.456	0.464	0.730	0.450	0.456	0.379
N	3,261	3,261	3,261	3,252	3,252	3,252

Note: The table displays estimates from OLS and IV regressions of the fraction donated on covariates. The variable “post entry” is 1 for the period from June 1st, 2017 onwards, and 0 otherwise. The data includes all auctions of actually worn soccer jerseys between June 19th, 2013, and November 6th, 2018 whose transaction price is larger than € 100 and smaller than € 1,000 (3,261 auctions). “Additional controls” include dummies for Champions League matches, Europa League matches, Serie A matches, Premier League matches, Liga matches, World Cup matches, finals, and the number of pictures displayed on the website. The reserve price is instrumented with the average reserve price across the other concurrent auctions (± 5 days) and, in columns 4-5 the average number of bidders across concurrent auctions, and in column 4 the average total number of bids placed in concurrent auctions. The First-stage F-stat is the Kleibergen-Paap rk Wald F statistic, whereas the weak-identification test is the Montiel-Pflueger robust test. All regressions include controls for the number of bidders, the number of bids placed as well as month and year fixed effects. In column 4 the Charity fixed effects are partialled out. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C14: Charitystars’s donations before and after the recapitalization. Weekly data

Quantile of weekly fraction donated (q)	(I)	(II)	(III)	(IV)	(V)	(VI)
	Q(20%)	Q(20%)	Q(50%)	Q(50%)	Q(80%)	Q(80%)
Post entry (0/1)	0.037 (0.070)	0.064 (0.069)	-0.199*** (0.062)	-0.183*** (0.062)	-0.090** (0.044)	-0.082* (0.044)
Average number of bidders, lag 1 week		Y		Y		Y
Average fraction donated, lag 1 week		Y		Y		Y
Adjusted R-squared	0.537	0.547	0.535	0.539	0.378	0.379
N	267	266	267	266	267	266

Note: The table displays estimates from OLS regressions of different quantiles of the weekly fraction donated. The variable “post entry” is 1 for the period from June 1st, 2017 onwards, and 0 otherwise. The data includes all auctions of actually worn soccer jerseys between June 19th, 2013, and November 6th, 2018 (3,968 auctions, 267 weeks in total). All regressions include a constant and month and year fixed effects. The qualitative results would not change using monthly data. Robust standard errors in parentheses.

* - $p < 0.1$; ** - $p < 0.05$; *** - $p < 0.01$.

Table C15: Number of bidders before and after the recapitalization

Number of bidders	Poisson regressions		IV for Reserve price
	(I)	(II)	(III)
Post entry (0/1)	-0.206*** (0.043)	-0.177*** (0.043)	-0.901*** (0.243)
Reserve price	0.000 (0.000)	-0.000** (0.000)	-0.008*** (0.001)
First-stage F-stat			191.747
Montiel-Pflueger robust test p-value			≤ 0.05
Over-id p-value			0.920
Additional Control			Y
Pseudo / Adjusted R-squared	0.065	0.076	0.129
N	3,261	3,261	3,252

Note: The table displays estimates from Poisson and IV regressions of the number of bidders on covariates. The variable “post entry” is 1 for the period from June 1st, 2017 onwards, and 0 otherwise. The data includes all auctions of actually worn soccer jerseys between June 19th, 2013, and November 6th, 2018 whose transaction price is larger than €100 and smaller than €1,000 (3,261 auctions). “Additional controls” include dummies for Champions League matches, Europa League matches, Serie A matches, Premier League matches, Liga matches, World Cup matches, finals and the number of pictures displayed on the website. The reserve price is instrumented with average reserve price and the average number of pictures displayed on the listing website across the other concurrent auctions (± 5 days). The First-stage F-stat is the Kleibergen-Paap rk Wald F statistic. All regressions include month and year fixed effects. In column VI the Charity fixed effects are partialled out. Pseudo R-squared is reported for columns 1 and 2. Robust standard errors in parentheses.

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

D Additional Figures

Figure D1: The webpage of a listing at the time of data collection

Title

Match Issued AC Milan 2014/15 Home Shirt Signed by Bonaventura

Auction rules Info request Keep me updated

Countdown

Expires Tuesday 07 June at 07:00
03 : 18 : 23 : 15

Charity

Play For Change
playforchange.org

Current price

£ 110 Total 5 Offers

Current bid by **Supermanfra** 2 hours and 31 minutes ago

Reserve price not met

MAKE YOUR BID

Minimum bid up: £ 5

85% Minimum percentage of the proceeds that will be donated to charity. How it works?

Pictures

% donated

Details Terms of Service Shipment Payment

This auction is for an AC Milan home shirt **issued** for the Italian midfielder Giacomo Bonaventura in the 2014/15 season. The player has also **signed** the back of the shirt.

Features:

- Red and black home match issued Lazio shirt with short sleeves
- Serie A Tim patch on right sleeve
- Milan crest on chest
- Size L, #28
- Name and number applied in thin plastic

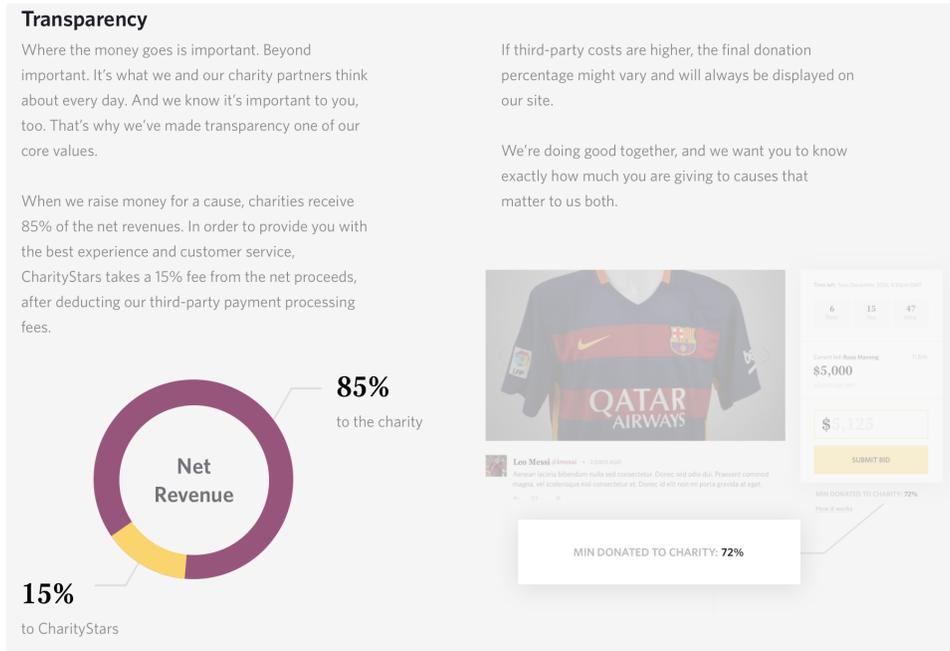
Description

The proceeds raised from this auction will support **Play for Change**

Conditions: The auction winner will be notified via email and will receive the item within 15 working days of payment being received. For more information, email enquiries@charitystars.com or ring us on 0203 301 5800.

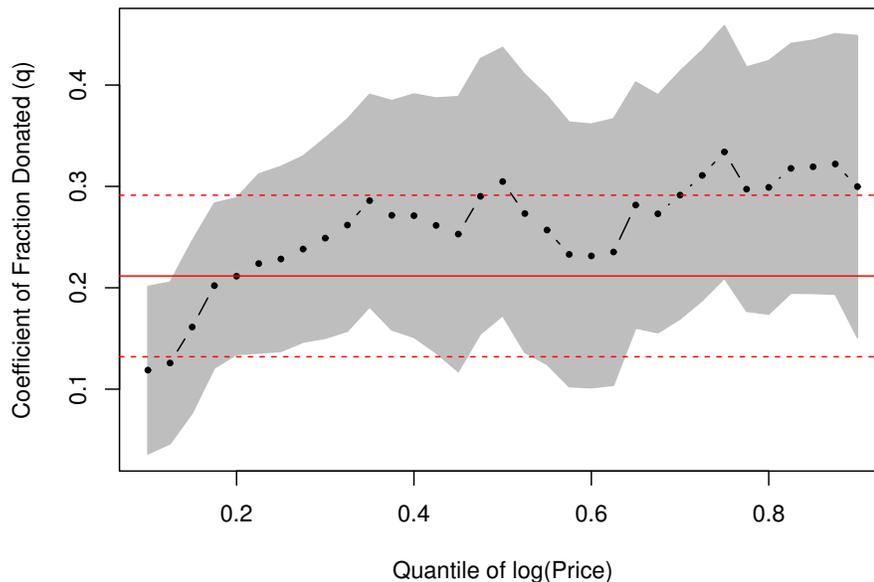
Note: Screenshot of a webpage of a running auction on Charitystars.com for an AC Milan jersey worn and signed by the player Giacomo Bonaventura. The standing price is GBP 110: this bid was placed by an Italian bidder with username "Supermanfra". A total of five bids are placed at this point. Although at the current highest bid the reserve price is not met, this can change by the end of the auction. The auction will be active for other 3 days and 18 hours and will expire on June 7th at 7AM. 85% of the proceeds will be donated to "Play for Change".

Figure D2: How the firm allocates the funds at the time of data collection



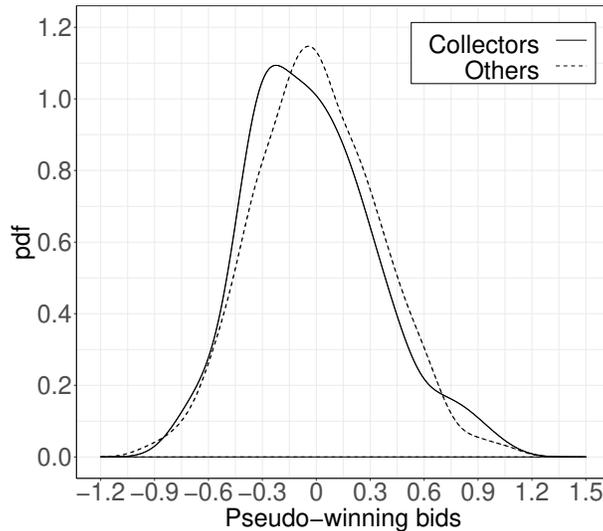
Note: Screenshot describing how the firm allocates the fraction donated at the time of scraping.

Figure D3: Plot of the coefficient for the fraction donated from a quantile regression



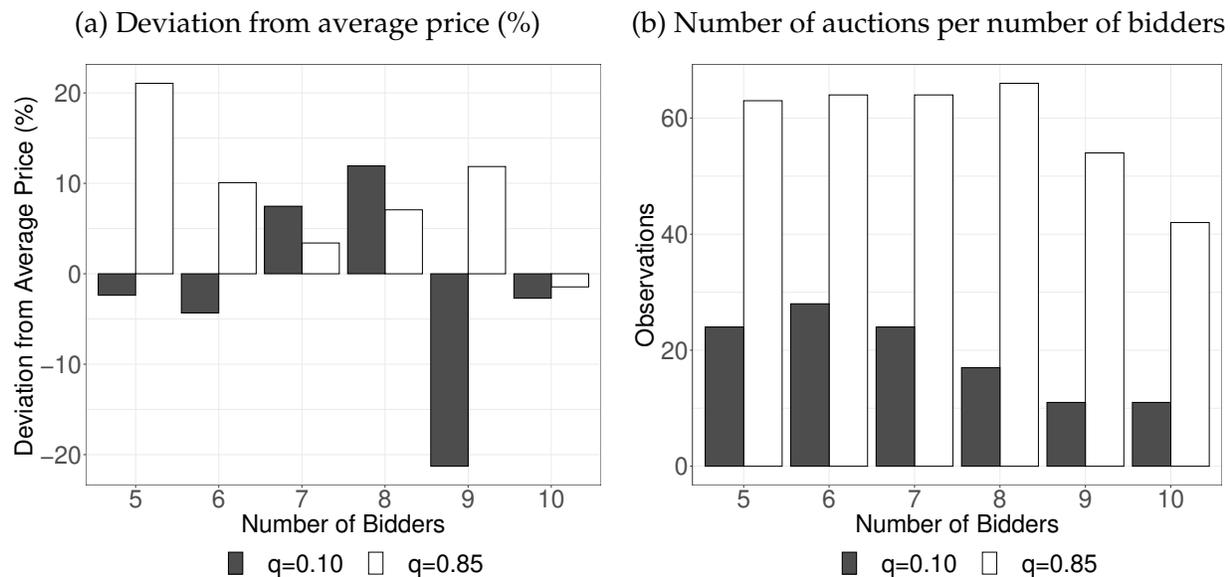
Note: The plot displays coefficients from quantile regressions of the logarithm of the transaction price on q and covariates as in the first column of Table C1 in the main text. The shaded regions is the confidence interval. The dashed (dotted) line reports the coefficient of the OLS regression (5% confidence interval). Appendix Table C1 shows the coefficients for each quantile. Only auctions with price between € 100 and € 1000. Bootstrapped standard errors with 400 repetitions.

Figure D4: Density of the homogenized transaction prices by returning winners vs non-returning winners



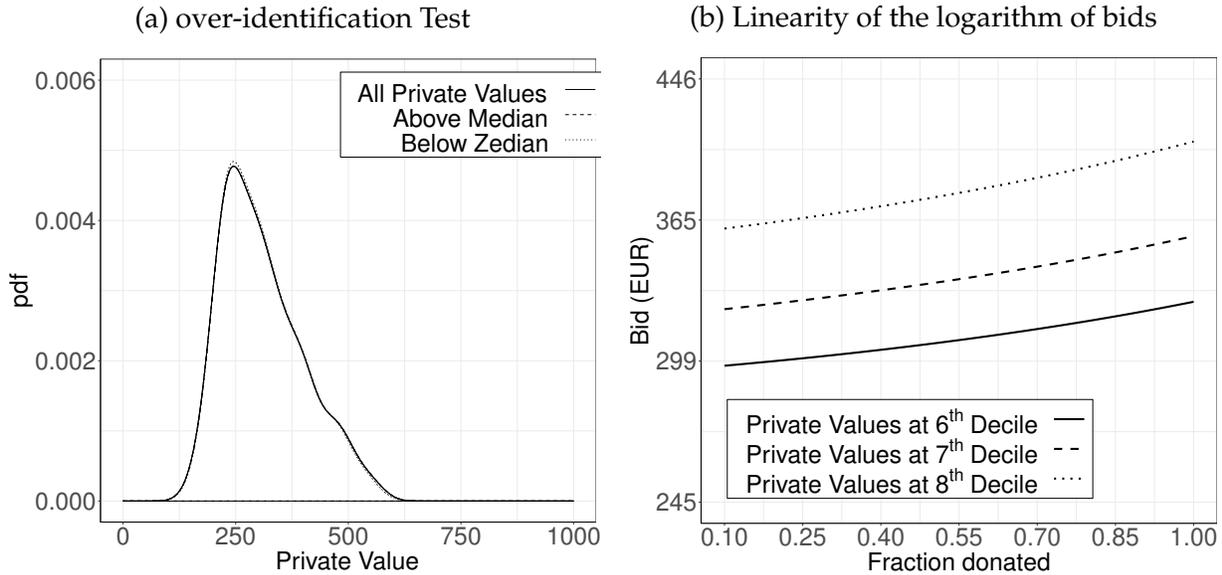
Note: The plot displays the density of the pseudo-winning bids from the first-step of the structural model distinguishing by returning winners. Returning winners (or collectors) are bidders who won at least 4 auctions (the median is 3). The Kolmogorov-Smirnov test does not reject the null hypothesis that the two densities are equal at 0.4097 level. The plot is obtained using only auctions with $q \in \{10\%, 85\%\}$. The plotted densities are computed using a Gaussian kernel and Silverman's rule-of-thumb bandwidths (Silverman, 1986).

Figure D5: Comparison between the model implied prices and observed average prices



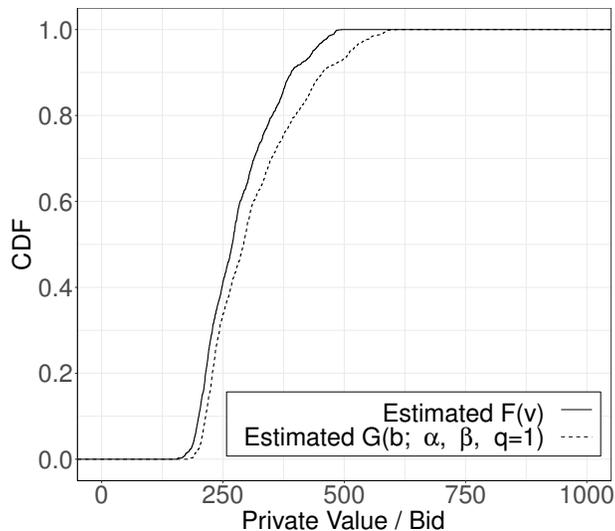
Note: Panel a. The barplot displays the percentage difference between the observed price in the data and the expected price implied by the model for different number of bidders. A positive number indicates that the model overstates prices. Panel b. The barplot displays the number of auctions such that the number of bidders joining the auction is equal to that indicated in the x axis.

Figure D6: Additional robustness checks



Note: Panel a. The plot compares the estimated densities in the main text (Main, solid line) with the density computed on two subsets of the moment conditions. The subset “Above Median” (“Below Median”) includes only the moment related to observations computed above (below or equal to) the median. The different sets of moments seem to produce the same densities. The KS-test does not reject the null hypothesis that the densities are equal at $p < 0.01$. Panel b. The plots displays the simulated natural logarithm of the bids computed at different deciles of the estimated $F(v)$ assuming heterogeneity at the the median value of the covariates in the estimation. The Y axis shows values in €. I test linearity by fitting a linear and a nonlinear model (second order polynomal) via ANOVA to address whether the nonlinear model explains a significantly larger amount of variance. The F-test does not reject the null (p-value = 0.428).

Figure D7: Overbidding with respect to private values



Note: The plot compares the distribution of bids with the distribution of private values at the estimated primitives. Distributions are simulated by drawing 200 private values from the estimated distribution of values, and using the estimated α and β , with $q = 1$.

E Robustness Checks for the Optimal Fraction Donated

I propose several robustness checks to the main text analysis. All estimates report robust standard errors. Confidence intervals for the optimal q are obtained through 401 bootstrap replications of the estimation algorithm with replacement.

Optimal Fraction Donated with More Covariates. I include all the variables in the dataset as in the fourth column of Table 1 by adding to the first-step regressions of both the demand and supply model the variables belonging to the groups “Additional Charity Dummies”, “League/Match Dummies” and “Time Dummies.” Figure E1 shows the optimal fraction donated by intersecting marginal revenues and marginal costs as in Section 7. On the supply side the marginal cost parameters are $\pi_1 = 229.275, SE : 11.822; \pi_2 = -400.940; SE : 55.084; \pi_3 = 187.354, SE : 53.151$, while on the demand side α is estimated to be 0.172 and β is 0.431 when the number of bidders is 16. The optimal fraction donated is $q^* = 0.20$ (95% C.I. [0.025,0.475]).

Optimal q^* by Type of Provider. I further investigate whether the optimal fraction donated varies consistently based on the type of provider. When available, I observe whether the object is provided by either a footballer, a coach or a charity (672 auctions). Because footballers and coaches are closely tied to certain charities, I separate the auctions in the sample in two based on whether the provider of the auctioned item is a private individual or not, and estimate marginal costs on each subsample in the same way as in Section 7.

The marginal cost for the whole group including footballers and charities are negative and upward sloping ($\pi_1 = 248.388, SE : 28.495; \pi_2 = -557.406; SE : 54.894; \pi_3 = 349.055, SE : 56.898$). Figure E2 plots the optimal q obtained for this group. I find that $q^* = 0.32$ (95% C.I. [0.045,0.420]), which is very close to that estimated in the full sample (see Figure 5a). The qualitative result does not change if I replicate the analysis to account for the auctions provided by charities (469 auctions, $\pi_1 = 259.095, SE : 42.792; \pi_2 = -677.876; SE : 321.572; \pi_3 = 478.420, SE : 323.874$). In this case, q^* is 0.36 (95% C.I. [0.045,0.435]).

Optimal q^* Using IVs. As the reserve price and the fraction donated are the result of bargaining between the provider of the item and Charitystars, in this section, I instrument the reserve price in the demand model and the fraction donated in the supply model. On the demand side, I perform a two-stage least square regression in place of equation 6.1; I instrument the reserve price with the average reserve price (in logs) and the average number of bids placed in concurrent auctions (within 5 days). The estimated α and β are 0.173 and 0.431. The F-test is large 33.269, and the over-identification test statistic has a p-value of 0.192 (Sargan test).

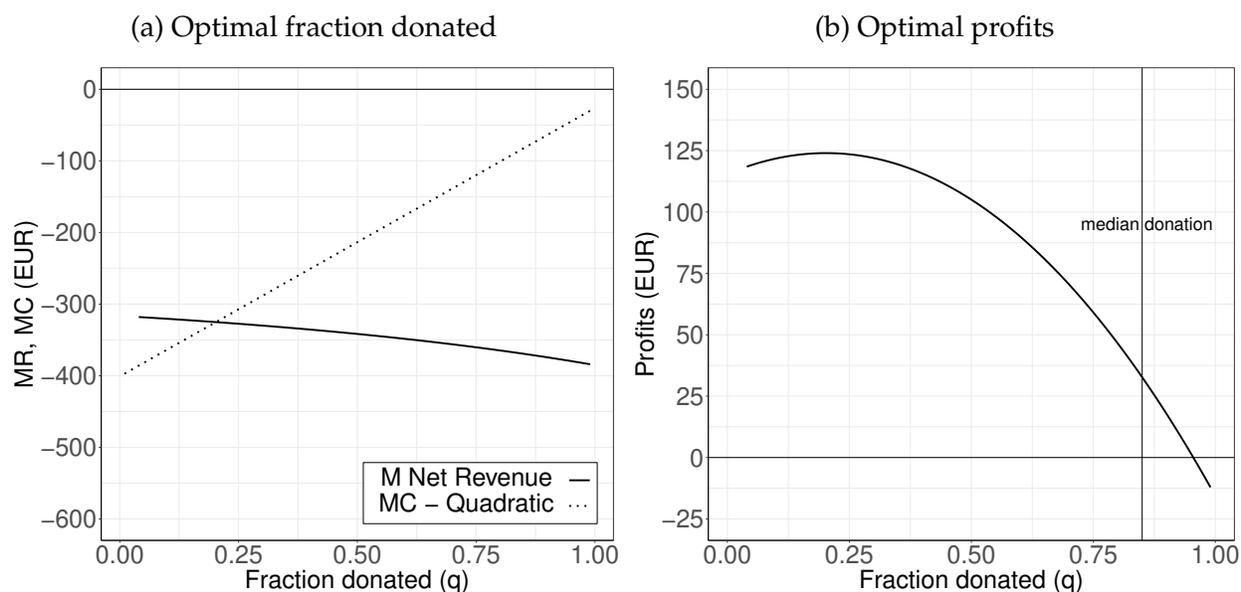
On the supply side, I follow the same steps in Section 7. In the last step, instead of performing an OLS regression of the net reserve price on a polynomial expansion of q , I instrument q and q^2 with the average fraction donated (and its squared value) and the average number of bids placed (and its squared value) across concurrent auctions (within 5 days). The estimated marginal cost parameters are $\pi_1 = 273.389, SE : 44.128; \pi_2 = -650.978; SE : 298.535; \pi_3 = 422.534, SE : 296.863$. The F-test for the first endogenous regressor (q) is 30.637 and for the second endogenous regressor (q^2) is 33.063. The over-identification test has a p-value of 0.907. Despite the strong first stages, the instruments would fail if the choice of the fraction donated and of the reserve price systematically responded to common shocks across concurrent auctions. I include the number of listings of jerseys from the same team in the previous 3 weeks and for the same player in the previous 2 weeks among the covariates to control for this issue.

Figure E3 plots both the marginal revenue and marginal cost curves (Panel a) and the expected profits attainable at different fraction donated (Panel b). Both plots indicate that the optimal fraction

donated is 0.30 (95% C.I. [0.025,0.455]).

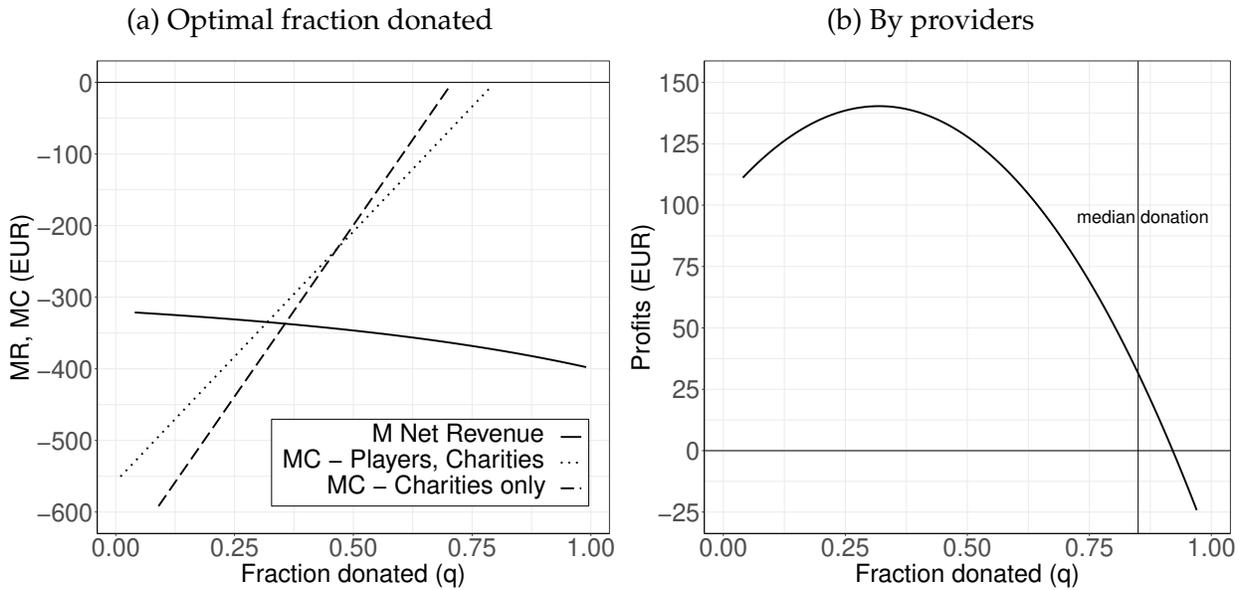
Optimal q^* with a Different Level of Heterogeneity. In the main paper, I homogenize all bids and reserve prices, and sum back the value of the heterogeneity from the median auction to determine both marginal revenues and marginal costs. In this section, I replicate the same analysis but considering the heterogeneity at the 1st and 3rd quartiles. The results are in Figure E4a (the parameters estimated in the quadratic-cost case are $\pi_1 = 176.845, SE : 11.346; \pi_2 = -320.638; SE : 61.724; \pi_3 = 158.392, SE : 60.704$, and the parameters in the cubic-cost case are $\pi_1 = 187.055, SE : 70.489; \pi_2 = -445.534; SE : 823.537; \pi_3 = 432.089, SE : 1738.863, \pi_4 = -166.111; SE : 1020.906$) and Figure E4c (the parameters estimated in the quadratic-cost case are $\pi_1 = 309.186, SE : 19.836; \pi_2 = -560.587; SE : 107.916; \pi_3 = 276.925, SE : 106.131$, and the parameters in the cubic-cost case are $\pi_1 = 327.037, SE : 123.24; \pi_2 = -778.947; SE : 1439.83; \pi_3 = 755.442, SE : 3040.149, \pi_4 = -290.42; SE : 1784.90$) respectively. The optimal donation for the 1st quartile case is 0.18 (95% C.I. [0.025,0.330]) while for the 3rd it is 0.27 (95% C.I. [0.030,0.420]).

Figure E1: Optimal q^* with more covariates



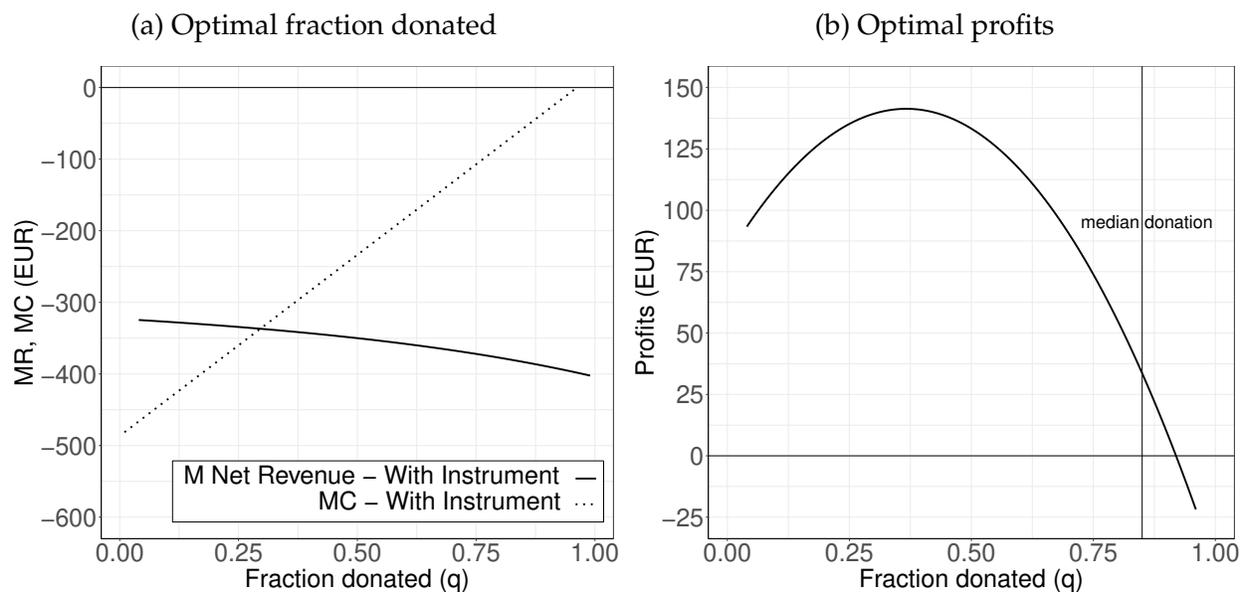
Note: The plot displays the optimal fraction donated as the intersection of marginal costs (dotted and dashed lines) and net benefits (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) and cubic polynomials (dashed line). Panel b. The plot displays how profits change with the fraction donated (q). The vertical line at 85% indicate the median donation by Charitystars. Unlike the main text analysis, all covariates in the fourth column of Table 1 are added to the first steps of both the demand and supply analyses. The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Profits are computed as net revenues minus costs as in the quadratic polynomials case. Marginal revenues and revenues assume that the number of potential bidders is 7 in both plots.

Figure E2: Optimal q^* by type of provider



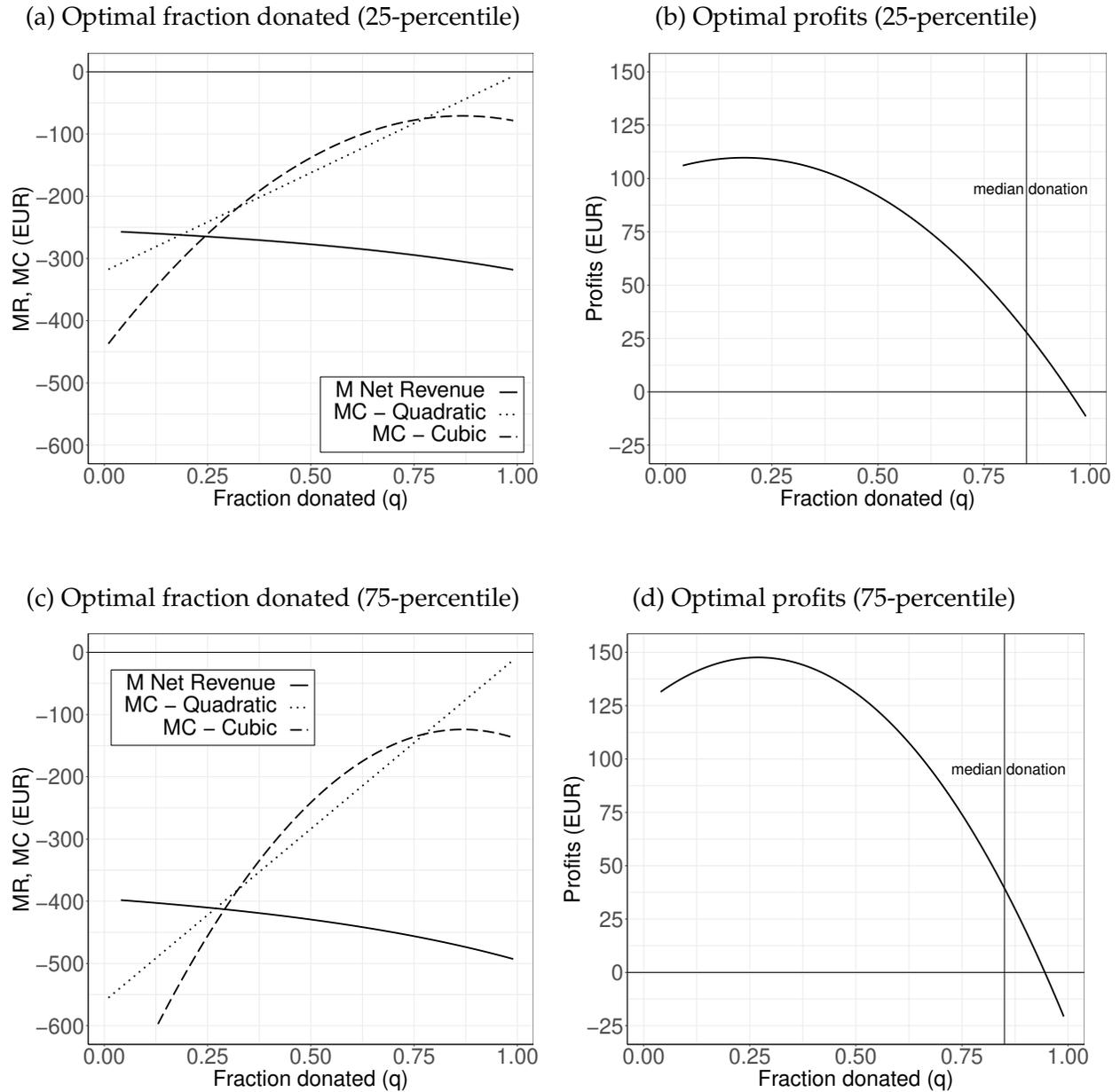
Note: The plot displays the optimal fraction donated as the intersection of marginal costs (dotted and dashed lines) and net benefits (solid line). The marginal costs are estimated using quadratic polynomials. Unlike the main text analysis, I limit the dataset to auctions of item provided by either charities (dashed line) or footballers and charities (dotted line). Panel b. The plot displays how profits change with the fraction donated (q). The vertical line at 85% indicate the median donation by Charitystars. The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Profits are computed as net revenues minus costs as in the quadratic polynomials case. Marginal revenues and revenues assume that the number of potential bidders is 7 in both plots.

Figure E3: Optimal q^* using instrumental variables



Note: The plot displays the optimal fraction donated as the intersection of marginal costs (dotted line) and net benefits (solid line). The marginal costs are estimated using quadratic polynomials (dotted line). Panel b. The plot displays how profits change with the fraction donated (q). The vertical line at 85% indicate the median donation by Charitystars. Unlike the main text analysis, I instrument the reserve price in the demand analysis with the average reserve price and the average number of bids placed in concurrent auctions. I similarly instrument the fraction donated in the supply analysis with the average fraction donated and the average number of bids. The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Profits are computed as net revenues minus costs as in the quadratic polynomials case. Marginal revenues and revenues assume that the number of potential bidders is 7 in both plots.

Figure E4: Optimal q^* with a different level of heterogeneity



The plot displays the optimal fraction donated as the intersection of marginal costs (dotted and dashed lines) and net benefits (solid line). The marginal costs are estimated using quadratic polynomials. Panel b. The plot displays how profits change with the fraction donated (q). The vertical line at 85% indicate the median donation by Charitystars. Unlike the main text analysis, I fit revenues and costs to represents either the 25th- or 75th- percentile of auction heterogeneity. The density $f(v)$ and the distribution $F(v)$ are approximated using a cubic spline. Profits are computed as net revenues minus costs as in the quadratic polynomials case. Marginal revenues and revenues assume that the number of potential bidders is 7 in all plots.

F Monte Carlo simulations

Objectives. The Monte Carlo simulations in this section fulfil two goals: (i) to show that the estimation routine described in Section 6 return consistent estimates of the parameters, and (ii) to support with some empirical evidence the claim that the estimates are not consistent when the fraction donated in the two auction types is very close.

Design of the experiments. There are two auction types (A and B) such that $q^A = .10$ and $q^B = .85$. Private values are generated for all bidders drawing from a uniform distribution in $[0, 1]$ in Tables F1 and F2 and in $[-1, 1]$ in Tables F3. There are 10 bidders in each auctions. They bid according to the bid function in equation 4.2. The true charitable parameters are $\alpha_0 = .25$ and $\beta_0 = .75$.

The steps of the estimation procedure are outlined below:

1. Draw values from the distribution $F(v)$ for each bidder in the two auctions. In total 20 values.
2. Compute the bids for each bidder in the two auctions. Save the winning bid in each auction.
3. Nonparametrically estimate the density of the winning bids (either by Triweight, or Gaussian Kernel). The bandwidth is chosen using the rule-of-thumb. Trimming follows Guerre *et al.* (2000) who suggested trimming observations close to $0.5 \times$ bandwidth to the boundary.⁵
4. Given the number of bidders ($n = 10$) invert the distribution of the winning bids to determine the distribution and density of the bids as in the second stage of the estimation procedure.
5. Compute the distribution and density of auctions of type A for each losing bids in the interval between the smallest winning bid and the largest winning bid of type A.
6. Compute the distribution and density of type B ($q = .85$) over 100,000 points.
7. Match the quantile of the distribution of type B with those of the distribution of type A through equation 5.1.
8. Find the couple (α, β) that minimizes the objective function equation 6.2 starting from a random seed. The search algorithm constraints the parameters in the unit interval.
9. Save the estimates and restart from 1.

These steps are repeated 401 times. The tables below report the mean, median, quantiles and root mean squared errors for α and β for each combination of parameters.

Results. First, let's asses the consistency of the estimates. Different experiments are reported in Tables F2 and F3, showing that the estimates are close to the true parameters. In particular, even with a small number of observations (the first line in each panel), the mean and medians are always within 3% of the true parameters.

These tables are composed by different panels: each panel refers to a different kernel used to estimate the distributions (and densities) of the winning bids. The Gaussian and Triweight kernels give similar results. Within each panel, the rows differ on the number of auctions used to estimate the primitives. The number of bidders in each auction is always constant and equal to 10. Since

⁵For the Gaussian case the $h_{pdf} = 1.06\sigma n^{-1/5}$ and $h_{CDF} = 1.06\sigma n^{-1/3}$ where $\sigma = \min\{\text{s.d.}(b_w^k), \text{IQR}/1.349\}$, where b_w^k is the vector of winning bid for auction of type k , and $h_{CDF} = 1.587\sigma n^{-1/3}$. For the triweight case $h_{pdf} = h_{CDF} = 2.978\sigma n^{-1/5}$ (Härdle, 1991, Li *et al.*, 2002, Li and Racine, 2007, Lu and Perrigne, 2008).

for each auction only the winning bid is used, I *empirically* consider the asymptotic properties of the estimator by looking at the rate at which the root mean squared error (RMSE) decreases as the number of auctions grows (i.e., comparing RMSE across columns).⁶ Comfortingly, this rate is close to \sqrt{n} for all experiments.

To study the consistency of the estimates when there is only limited variation over q across auctions I run similar experiments varying q instead of the nonparametric kernel. From Table F1 it is clear that α and β cannot be estimated consistently when $q^A \simeq q^B$ as the mean and median of the estimated parameters are about 0 and .50 instead of .25 and .75 for α and β respectively.

Table F1: Distance between q^A and q^B – Monte Carlo simulations

T^A	T^B	μ_α	μ_β	Med $_\alpha$	Med $_\beta$	25% $_\alpha$	75% $_\alpha$	25% $_\beta$	25% $_\beta$
$q_A = 80\%, q_B = 85\%$									
500		0.0069	0.5333	0.0000	0.5328	0.0000	0.0000	0.5053	0.5589
1000		0.0094	0.5355	0.0000	0.5302	0.0000	0.0078	0.5114	0.5560
$q_A = 78\%, q_B = 85\%$									
500		0.0158	0.5414	0.0000	0.5350	0.0000	0.0151	0.5137	0.5606
1000		0.0227	0.5477	0.0028	0.5376	0.0000	0.0348	0.5181	0.5667
$q_A = 50\%, q_B = 85\%$									
500		0.2027	0.7086	0.1914	0.6991	0.1360	0.2520	0.6455	0.7579
1000		0.2154	0.7196	0.2071	0.7132	0.1696	0.2636	0.6763	0.7620
$q_A = 20\%, q_B = 85\%$									
500		0.2468	0.7467	0.2383	0.7398	0.1984	0.2891	0.7033	0.7852
1000		0.2462	0.7463	0.2445	0.7444	0.2166	0.2764	0.7186	0.7730

Note: Monte Carlo simulations of the second and third step of the estimation process. Auction types are denoted by A and B . Each panel shows the estimated parameters for different percentage donated. The bandwidths in step 2 are computed with a Gaussian Kernel. The data is generated according to $\alpha = 25\%$, $\beta = 75\%$ and $F(v)$ is assumed uniform in $[0, 1]$. Each auction has 10 bidders. 401 repetitions.

⁶I am analyzing the asymptotic properties of this class of estimators theoretically in another project, which is still a work in progress.

Table F2: Monte Carlo simulation 1

T^A	T^B	μ_α	μ_β	Med $_\alpha$	Med $_\beta$	25% $_\alpha$	75% $_\alpha$	25% $_\beta$	10% $_\alpha$	90% $_\alpha$	10% $_\beta$	90% $_\beta$	RMSE $_\alpha$	RMSE $_\beta$
Gaussian kernel														
34	112	0.2760	0.7723	0.2681	0.7706	0.1513	0.4202	0.6577	0.0631	0.4954	0.5846	0.9900	0.1587	0.1469
172	560	0.2682	0.7658	0.2647	0.7627	0.2160	0.3195	0.7176	0.1725	0.3699	0.6781	0.8583	0.0789	0.0726
	100	0.2637	0.7615	0.2449	0.7442	0.1759	0.3506	0.6802	0.1148	0.4459	0.6234	0.9345	0.1225	0.1135
	500	0.2507	0.7500	0.2428	0.7452	0.2089	0.2914	0.7122	0.1813	0.3258	0.6881	0.8190	0.0586	0.0534
	1000	0.2498	0.7494	0.2475	0.7470	0.2227	0.2764	0.7253	0.1965	0.3056	0.7010	0.8020	0.0412	0.0377
Triweighth kernel														
34	112	0.2318	0.7391	0.2051	0.7136	0.1172	0.3500	0.6281	0.0460	0.4725	0.5644	0.9848	0.1522	0.1453
172	560	0.2310	0.7346	0.2267	0.7309	0.1797	0.2802	0.6875	0.1347	0.3323	0.6421	0.8277	0.0767	0.0718
	100	0.2855	0.7837	0.2820	0.7797	0.1953	0.3742	0.6990	0.1172	0.4853	0.6293	0.9806	0.1314	0.1238
	500	0.2547	0.7543	0.2535	0.7522	0.2115	0.2910	0.7145	0.1855	0.3304	0.6866	0.8254	0.0579	0.0536
	1000	0.2503	0.7507	0.2507	0.7503	0.2209	0.2765	0.7233	0.1998	0.3031	0.7054	0.7996	0.0412	0.0378

Note: Monte Carlo simulations of the second and third step of the estimation process. Auction types are denoted by A and B . The bandwidths in step 2 are computed either with a Gaussian Kernel (top panel) or with a Triweighth kernel (bottom panel). The data is generated according to $\alpha = 25\%$, $\beta = 75\%$, $q^A = 10\%$, $q^B = 85\%$ and $F(v)$ is assumed uniform in $[0, 1]$. Each auction has 10 bidders. 401 repetitions.

Table F3: Monte Carlo simulation 2

T^A	T^B	μ_α	μ_β	Med $_\alpha$	Med $_\beta$	25% $_\alpha$	75% $_\alpha$	25% $_\beta$	10% $_\alpha$	90% $_\alpha$	10% $_\beta$	90% $_\beta$	RMSE $_\alpha$	RMSE $_\beta$
Gaussian kernel														
34	112	0.2785	0.7687	0.2716	0.7639	0.1557	0.4026	0.6717	0.0812	0.4961	0.6013	0.9790	0.1580	0.1350
172	560	0.2661	0.7611	0.2636	0.7592	0.2169	0.3128	0.7194	0.1763	0.3588	0.6851	0.8410	0.0735	0.0627
	500	0.2513	0.7492	0.2472	0.7477	0.2131	0.2871	0.7191	0.1887	0.3203	0.6949	0.8064	0.0537	0.0449
	1000	0.2506	0.7491	0.2480	0.7469	0.2255	0.2755	0.7282	0.2023	0.3035	0.7080	0.7919	0.0380	0.0319
Triweighth kernel														
34	112	0.2342	0.7586	0.2166	0.7450	0.1206	0.3501	0.6429	0.0543	0.4388	0.5805	0.9900	0.1416	0.1473
172	0.2341	0.2341	0.7499	0.2323	0.7481	0.1777	0.2820	0.6968	0.1422	0.3304	0.6588	0.8457	0.0753	0.0722
	500	0.2673	0.7659	0.2632	0.7636	0.2262	0.3055	0.7289	0.1952	0.3457	0.6976	0.8355	0.0591	0.0549
	1000	0.2583	0.7587	0.2578	0.7589	0.2305	0.2838	0.7349	0.2103	0.3110	0.7127	0.8025	0.0403	0.0364

Note: Monte Carlo simulations of the second and third step of the estimation process. Auction types are denoted by A and B . The bandwidths in step 2 are computed either with a Gaussian Kernel (top panel) or with a Triweighth kernel (bottom panel). The data is generated according to $\alpha = 25\%$, $\beta = 75\%$, $q^A = 10\%$, $q^B = 85\%$ and $F(v)$ is assumed uniform in $[-1, 1]$. Each auction has 10 bidders. 401 repetitions.

References in the Online Appendix

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