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CARING OR PRETENDING TO CARE? SOCIAL IMPACT, FIRMS' OBJECTIVES, AND WELFARE

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Caring or Pretending to Care? Social Impact, Firms' Objectives, and Welfare*

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Abstract

Many firms claim that "social impact" influences their strategies. This paper develops a structural model that quantifies social impact as the sum of surpluses to a firm and its stakeholders. With data from a for-profit firm whose prosocial expenditures are measurable and salient to consumers, the analysis shows that the firm spends prosocially beyond profit maximization, thereby increasing welfare substantially. Incentivizing a standard profit-maximizing firm to behave similarly would require subsidies amounting to 58% of its prosocial expenditures because consumers' willingness to pay is relatively inelastic to prosocial expenses. Therefore, social impact resembles a self-imposed welfare-enhancing tax with limited pass-through.

JEL classifications: L21, D64, C14
Keywords: benefit corporation law, social impact, welfare analysis, firms' objectives, externalities, structural estimation

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1 Introduction

The standard view on firms' objectives separates firms based on their initial sin: for-profit firms on the one hand and nonprofit firms on the other. One argument in favor of this view relates nonprofits to activities with low-private and high-social returns, while for-profits' sole concern is their private returns. This dichotomous view is changing. Mounting evidence shows that nonprofits behave like for-profit firms; indeed, several studies find that such firms have no greater regard for consumer or employee welfare than similar for-profits.[1] The past decade has witnessed the opposite trend. Today, for-profits increasingly claim to benefit society for engaging with various stakeholders, such as consumers, supply chain operators, and the environment. For instance, Patagonia, a sportswear company, sources its inputs from only environmentally conscious producers. This paper investigates this changing view by studying the welfare implications of for-profit firms' social missions.

This paper's main contribution is to frame social impact as a tradeoff between the costs of prosocial programs, which are borne within a firm, and their benefits, which extend to agents operating outside the firm. This framework can explain why some firms' decisions fail to increase profits (e.g., Margolis *et al.*, 2007), as these decisions may be made in the interest of third parties. This framework also provides an exact definition of social impact, namely, the aggregate change in the surpluses of all affected agents, including the firm itself.[2] Thus, measuring social impact requires data on both stakeholders' identities and payoffs and on the costs and returns of each corporate decision, which are typically unavailable. Moreover, even with this information, the endogeneity of a firm's social mission to its profit-making activities calls for a new approach to measuring social impact that excludes greenwashing (Bénabou and Tirole, 2010).

This paper studies a single market with suitable characteristics for assessing social impact. The focus is on a for-profit social impact firm called Charitystars, which auctions celebrity belongings and donates a fraction of the transaction price to charities.[3] The social good

[1] An extensive body of literature finds no substantial differences across U.S. for-profit and nonprofit hospitals in terms of pricing (e.g., Dranove, 1988, Keeler *et al.*, 1999), anticompetitive conducts and mergers (e.g., Blackstone and Fuhr, 1993, Vita and Sacher, 2001, Capps *et al.*, 2020), care quality, provision of uncompensated care, and technology adoption (e.g., Sloan, 1998). There are also no clear differences in the satisfaction of workers across nonprofit and for-profit firms (e.g., Emanuele and Higgins, 2000, Bailly and Chapelle, 2013).

[2] The word "social impact" has many interpretations. In economics, most analyses focus on whether a firm internalizes the consumer surplus that it generates (e.g., Dewatripont and Tirole, 2019, Duarte *et al.*, 2020), disregarding other agents. The corresponding legal definition is vague, even though determining whether a firm benefits society is a legal requirement for a benefit corporation (BC) firm – a firm incorporated with both for-profit and social missions. Legal scholars argue that phrases in incorporation articles, such as "impacting society and the environment," are empty without a methodology to assess impact (Westaway and Sampselle, 2012). In addition, lack of priority across stakeholders invalidates any legal defense of BCs (Callison, 2012).

[3] Charitystars is an international internet platform with offices in London, Milan, and Los Angeles, and $4m in equity. The company is owned by its funding members, who are also managers in the company, and

created by the firm – its donations – is salient to consumers, and the auction environment simplifies the estimation of consumer surplus. The firm purchases the auctioned items from the same charities receiving the donations (or a connected celebrity). Procurement costs are observable, which reveals how costs vary with the fraction donated. Therefore, all the elements needed to learn about the consequences of the social impact tradeoff on total welfare – the sum of consumer surplus, firm's profits, and fundraising – are available.

Exploiting a structural model of supply and demand and a change in Charitystars's capital structure, the analysis finds that Charitystars has social motives beyond profitability. Because consumers and suppliers value charitable donations, donating is desirable even for a standard profit-maximizing firm – a form of greenwashing (e.g., Lyon and Maxwell, 2011). However, Charitystars goes much further, and the firm would double its profits at the profit-maximizing donation rate (25% of revenues). Shifting to this rate would halve welfare in the economy from a level where welfare is three-quarters of its highest possible value. Due to the estimated mild pass-through of donations to bids, inducing a standard profit-maximizing firm to achieve the observed welfare level would require €0.58 of subsidies for each euro bidders donate; €0.86 would be required to reach the highest welfare level. Therefore, social impact acts like a tax that consumers do not (fully) internalize.

Donations are only one example of the social goods that firms generate beyond making profits. More generally, this framework extends to dealing with various stakeholders such as employees, suppliers, or the environment. Thus, all businesses need to address similar tradeoffs. Additionally, this tradeoff is important for policy as it differentiates greenwashers from genuinely caring firms, which are the subject of recent regulations. The introduction of the "benefit corporation" (BC) legal status, which was intended to defend for-profit firms' prosocial motives from mission-changing takeovers suggests that genuinely caring firms do indeed exist and that legislators want to promote them as they might give back to society.[4] Nevertheless, there is no taxonomy to identify these firms. The case of Charitystars exposes the critical aspects of this identification problem and its policy implications.

Methodologically, Charitystars faces a tradeoff between increasing donations to stimulate the demand of altruistic bidders and obtain smaller procurement costs from suppliers, and decreasing donations to earn more from each auction. Descriptive statistics show that this tradeoff exists. However, since the elasticities of demand and procurement costs to donations are unobservable from the data alone, this paper builds a structural model to

other investors. The company generated over $11 million for charities and nonprofit organizations in 2013–20.

[4]The Dodge vs. Ford Motor Co. court case of 1919 held that "a corporation is organized [...] primarily for the profit of the stockholders." BC firms pursue both profits and social missions, sheltering their managers from legal suits for diverting funds to other stakeholders. Despite being a recent phenomenon, BC firms are growing fast. For instance, Dorff *et al.* (2021) report that early-stage investments in Delaware-registered public BC firms grew from $139.2 m in 2014 to $870.7 m in 2019, totaling over $2.5bn in this period.

examine the firm's objectives. The model exploits variation in donations to estimate both consumers' willingness to pay and procurement costs.

The demand-side model features impurely altruistic consumers (Andreoni, 1990) who derive utility from their donations when they win an auction and from those of the winners when they lose (Engers and McManus, 2007). Consistent with evidence from eBay auctions showing that charity auction prices can be lower than prices in similar noncharity auctions (Elfenbein and McManus, 2010), the model shows that increasing the fraction donated can decrease prices if the extra utility from another bidder's donation exceeds that from winning. The resulting bid shading underscores the importance of identifying consumer preferences to inspect the auctioneer's strategy and changes in consumer surplus.

To quantify how altruistic preferences impact prices in Charitystars's auctions, the first-order conditions of the bidder's problem decompose consumption value into the payment net of the satisfaction gained from donating, and the utility accruing to other bidders from the winning bidder's donation. Since these two terms are linear in the altruistic parameters, variation in the fraction donated across auctions identifies preferences under the assumption that a bidder's consumption value for the auctioned item is independent of the fraction donated. An out-of-sample analysis tests and does not reject this assumption.

The demand model fits the data well, as its estimated expected revenues are within 10% of the realized revenues. On Charitystars, prices command only a small premium as bidders' willingness to pay increases with the fraction donated. However, donations carry a high direct cost in terms of foregone revenues: a counterfactual scenario where the firm does not donate shows that the average net revenue loss is as high as €250 per listing, or more than 60% of the average transaction price. Thus, considering only consumer preferences, the firm would be better off if it offered regular non-charity auctions.

Regarding the supply side, the firm contracts with the item provider over the amount paid upfront and the fraction donated from the auction. Since reserve prices are set to cover the upfront payment – an information provided by the firm's advisors – variation in reserve prices identifies marginal costs. The analysis finds that procurement costs decrease in the fraction donated, implying negative marginal costs, as illustrated in a bargaining model. Linking costs and revenues, the profit-maximizing donation rate is about 25% of the transaction price, yet the average donation is 70%, indicating that Charitystars is far from a pure profit maximizing firm.

Several of the explanations that could reconcile Charitystars's behavior seem implausible. First, consistent with related empirical papers (e.g., Elfenbein and McManus, 2010), the raw data suggest that bids increase only slightly with the fraction donated, making the belief of an especially elastic demand unlikely. Second, there is little scope for reputation building, as higher donations in a period are not associated with more auctions or bidders in future periods (the two sides of the market).[5] Empirical evidence supporting the claim that Charitystars also cares about its charitable fundraising comes from its strategy change after a venture capital (VC) fund purchased shares in the firm. The VC fund invested to receive a capital gain, which shifted the firm's objectives toward profits. As a result, the average fraction donated decreased from 70% to approximately 25% after the entry, increasing the firm's net revenues without adversely impacting its costs, number of bidders, or number of auctions. This finding points to donations as an additional objective of the firm.[6]

Legislators passed the benefit corporation (BC) status to legally defend firms' social missions. This legal status requires firms to provide evidence that they are not greenwashers by detailing the fulfillment of their social missions in their yearly reports. However, less than 10% of BC firms do so because of legal fees and bureaucratic burdens (e.g., Murray, 2015, Vaughan and Arsneault, 2018, Wilburn and Wilburn, 2019). Thus, it is possible that only firms whose social goods are either particularly profitable or inexpensive apply to the BC status. Firms that go beyond profit maximization, such as Charitystars, may instead opt for a for-profit status, which has fewer legal requirements (e.g., MacLeod Heminway, 2017), and also allows for firm restructuring, which implies higher sale prices for shareholders. Thus, this policy may fail to promote prosocial firms due to selection (e.g., Bonneton, 2020).

The counterfactual results suggest that a matched subsidy similar to most of the charitable deductions available to individual taxpayers across Western countries can induce a fully for-profit firm to behave like Charitystars.[7] While such subsidies for for-profits are rare, nonprofits commonly receive fiscal advantages despite their dubious contributions to consumer welfare (e.g., Duarte *et al.*, 2020), and recent evidence suggests that corporations use tax-exempt donations to influence politicians (Bertrand *et al.*, 2020). For instance, the U.S. nonprofit sector received an estimated $137 bn in tax exemptions and deductions in 2015 (Jon, 2019). By contrast, the results in this paper support tax advantages for social impact rather than for legal status, similar to the rewards given to firms abating pollution

[5]Other examined explanations include the role of omitted variables bias in estimation, competition with other firms, managerial costs, and different bargaining weights across procurers. Finally, anecdotal evidence excludes that the high donations served to attract external investors.

[6]This paper add a new channel to a growing literature that relates failures to maximize profits to managerial costs (Ellison *et al.*, 2016, DellaVigna and Gentzkow, 2019), shareholder welfare (Hart and Zingales, 2017, Kaul and Luo, 2018, Broccardo *et al.*, 2020), and behavioral factors (Ellison, 2006, Hortaçsu *et al.*, 2019). Suboptimal choices are also observed in the National Football League as coaches do not always maximize the probability of victory (Romer, 2006), and teams often waste their top picks at the annual draft (Massey and Thaler, 2013).

[7]Although workers positively respond to intrinsic incentives (e.g., Kolstad, 2013), extrinsic incentives can reduce the prosocial efforts of motivated agents if they limit the signaling value of their prosocial actions (e.g., Ariely *et al.*, 2009, Cassar and Meier, 2018, Cassar, 2019). However, how firms respond to these incentives is still an open question, which may depend on the interaction between decision-makers' motivations (e.g., Levit, 2019, Fioretti *et al.*, 2021) and a firm's governance (e.g., Glaeser, 2002, Besley and Ghatak, 2005).

under the EU Emission Trading System (e.g., Colmer *et al.*, 2020). However, social impact is more heterogeneous and harder to measure than pollution. Applications of similar policies will depend on the reliability of the social impact measures, as rewards based on indices can distort firm strategies and have unintended consequences (Holmstrom and Milgrom, 1991).[8] Thus, by defining social impact and its data requirements, this paper offers a first step to reconsidering policies targeting the sustainability of the social mission of for-profits.

This paper is structured as follows. Section 2 describes Charitystars's business and data, and Sections 3 and 4 examine its demand and supply sides, respectively, while Section 5 analyses the firm's behavior, examines its objectives and discusses the consequences of social impact for policy and welfare. Section 6 concludes the paper.

2 Company Background and Data

Charitystars is a for-profit internet company that helps charities fundraise by offering charity auctions of celebrity memorabilia. Auctioned items vary considerably, ranging from VIP seats at sporting events to art and collectibles. Soccer items represent one of the most popular item categories with over 4,000 auctions held between 2015 and 2017. Moreover, Charitystars is a de facto monopolist in the market for worn and signed soccer jerseys, which is the focus in this paper, as alternative platforms have a considerably smaller market for these items (e.g., eBay).

Auction format. On Charitystars, the highest bidder wins the auctioned item and pays his or her bid. The transaction price is then shared between Charitystars and a charity according to a known sharing rule. If a fraction q of the price is donated, the firm keeps $1 - q$ as net revenues. The fraction donated and the awarded charity are known to all the bidders before the auction starts. The winner also receives a certificate guaranteeing the donation.

Each of Charitystars's auctions involve a single item and employ an open, ascending-bid format analogous to that of eBay. Moreover, bidders can submit proxy bids instead of standard bids. Once a proxy bid is set, Charitystars issues a bid equal to the smaller of the standing price and the highest competing proxy bid plus a minimum increment. Importantly, the auction countdown is automatically extended by 4 minutes anytime a bid is placed during the last 4 minutes of the auction. This effectively prevents sniping.

All the auction 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 of each item shows pictures of the item on the left side of the screen. Bidders can view a short description and information

[8] Kotsantonis and Serafeim (2019) suggest that ESG indices are biased and inconsistently measured. In this case pay-for-performance contracts can incentivize firms to game such indices (e.g., Fioretti and Wang, 2022).

on the recipient charity at the bottom of the page. The screenshot of a typical listing is in the online appendix (Figure D1).

Procurement. The item description in each listing identifies the soccer personality, team, or charity that procured the item. The item procurer and the recipient charity are either the same individual or closely linked. For instance, the online appendix presents an auction sponsored by a footballer who provided a jersey worn by an ex-teammate to raise funds for his charity (Figure D2).

Talks with advisors and shareholders of the company revealed two important pieces of information about Charitystars's business. First, Charitystars purchases items from procurers by paying them an upfront payment, which is then also transferred to the chosen charity. The amount of this payment depends on the fraction donated , which is negotiated between Charitystars and the provider. Therefore, auctions represent only a portion of the funds raised by the charities. For this reason, Charitystars calls the donated fraction of each auction the "minimum donation to the charity." Second, to avoid losses, Charitystars sets a reserve price for soccer jersey auctions such that the portion of the reserve price that is kept by the firm is equal to its upfront payment. Although the website does not report the payment associated with each listing, it can be recovered from the reserve price.[9]

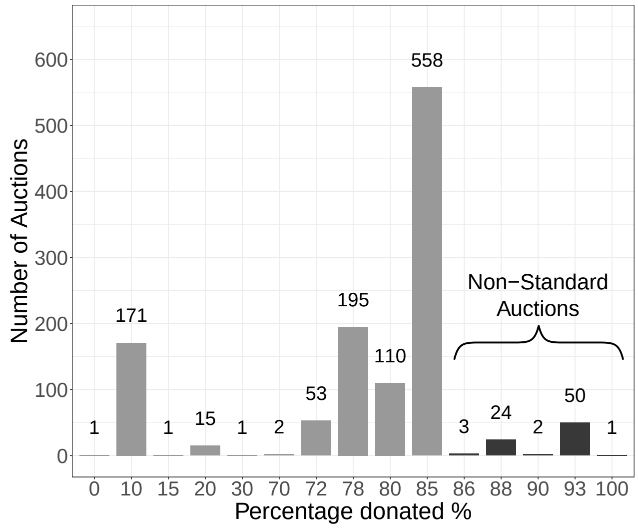
Data. The dataset used by this study contains auctions of authentic soccer jerseys sold over two consecutive seasons between July 1, 2015 and June 12, 2017. Figure 1 reports the number of auctions for each donation percentage. Auctions where more than 85% of the sale price was donated are disregarded in the analysis because they correspond to special events, as indicated in a screenshot of the FAQs reported in the online appendix (Figure D3). Throughout the paper, q denotes the fraction donated.

For each auction, all the bids placed, the date and time of each bid, the nationality of each bidder, and the awarded charity are observed. The starting prices and dates are unknown, and the number of days between the first bid and the closing day are used as a proxy for auction length, which, anecdotally, is between one and two weeks. The analyses focus on listings of sold items with at least two bidders, with transaction prices ranging from €100 - €1,000,[10] and with minimum raises below €30 (1,107 auctions in total). The average minimum raise is negligible (less than €2.00), and the transaction price is greater than the reserve price for more than 95% of the listings. On average (median) the winning bid is 2.9 (2) times greater than the reserve price. Online Appendix B describe the dataset in detail.

[9] During an auction, bidders only know if the current standing price is above the reserve price, which, however, can be found in the website's HTML code. The dataset does not have information on the starting bids, but, anecdotally, they are below their corresponding reserve prices and close to €0. Knowledge of the reserve price does not affect optimal bidding in the second-price auction model developed in Section 3.2.

[10] These limits are the 7.5^{th} and 92.5^{th} percentiles of prices. Different trimming does not affect the results.

Figure 1: Number of auctions by percentage donated



Note: This bar plot displays the number of auctions available in the dataset by percentage donated. The plot includes only auctions of items with prices between €100 and €1,000 with reserve prices greater than 0, with at least two bidders and with minimum increments less than or equal to €30. The plot further excludes auctions of jerseys belonging to second-division teams. There are 1,187 auctions in total. The firm 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 bars).

3 Demand: The Pass-Through of Charitable Donations

This section studies how bidders react to different donation levels. This is important for estimating (i) how elastic is the demand faced by the auctioneer, and (ii) how consumer surplus vary with donations. This analysis starts with an empirical study of the bids placed (Section 3.1), and then develops (Section 3.2), identifies (Section 3.3) and estimates (Section 3.4) a structural model of strategic behavior for charity auctions.

3.1 Descriptive Evidence

Intensive margin. Consider the following specification to examine whether higher transaction prices are associated with higher fractions donated, indicated by q:

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

where t indexes the focal auction. The jerseys are quite comparable across different fractions donated, as the latter variable is not highly correlated with the quality of the player wearing a given jersey.[11] Since the payoff to the awarded charity includes both the direct payment and the donation, providing a better jersey does not necessarily imply a higher fraction donated, as the provider could prefer a larger direct payment instead.

Table 1 displays the results. Each column includes different variables in $\mathbf{x}_t$, which controls for the characteristics of auctions, listings, players, teams and charities as well as month, year and day-of-the-week fixed effects. The estimates indicate that a 0.1 increase in the fraction donated is associated with a price increase between €6.8 and €9.6 (2% of the average price); this points to a positive but small correlation between bids and donations.

Table 1: Transaction prices and fractions donated

Transaction price	(I)	(II)	(III)	(IV)	(V)
Fraction donated (q)	95.990***	93.850***	88.082***	96.070***	67.963***
	(16.525)	(16.672)	(16.884)	(18.144)	(19.861)
Reserve price	0.800***	0.802***	0.787***	0.774***	0.760***
	(0.037)	(0.037)	(0.039)	(0.041)	(0.044)
Number of bidders	14.017***	14.024***	13.045***	12.654***	11.469***
	(1.463)	(1.471)	(1.489)	(1.494)	(1.526)
Main variables	✓	✓	✓	✓	✓
Add. charity dummies		✓	✓	✓	✓
League/match dummies			✓	✓	✓
Time dummies				✓	✓
Charity fixed effects					✓
Adjusted R-squared	0.517	0.519	0.534	0.546	0.575
BIC	14,120	14,146	14,209	14,286	14,407
N	1,107	1,107	1,107	1,107	1,107

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

Note: OLS regression of the transaction price on covariates. The control variables are defined in the online appendix. Robust standard errors in parenthesis.

The coefficient γ_q is not consistently estimated if unobserved characteristics affect the negotiation between the item provider and Charitystars. Thus, Table 1 could erroneously suggest that bidders care about giving, while in actuality they only care about these unaccounted characteristics. Addressing this endogeneity requires isolating Charitystars's contributions toward the realized q from that of the corresponding item provider. A similar identification problem concerns the coefficient of the reserve price, which is included in $\mathbf{x}_t$.

[11] Player quality data sourced from the Fifa videogames over the previous five soccer seasons display a low Spearman correlation with q, ranging between -0.07 and 0. The correlation between q and the other covariates is also small (lower than $|0.25|$).

The fact that Charitystars negotiates individually with each item provider is a source of exogenous variation, as the contract between Charitystars and provider i does not affect the negotiations the firm has with provider j. Therefore, the negotiation outcomes of other simultaneous auctions inform the preferred fraction donated of Charitystars and, conditional on covariates, are orthogonal to the preferred fraction donated of the provider involved in the negotiation. Thus, the average fraction donated of all concurrent auctions ending within five days from an auction's deadline is a plausible instrument for the fraction donated in that auction. A similar reasoning applies to reserve prices.

Any correlation across auctions would invalidate the instrument. One way in which correlation is introduced is if a provider strikes a deal for multiple objects simultaneously. However, 99% (90%) of the auction listings have at least 6 (10) auctions closing within five days of their deadlines, with a median of 27 concurrent auctions (cf. Figure D5 in the online appendix). It is therefore unlikely that the average fraction donated across concurrent auctions meaningfully and systematically reflects the preferred fraction donated by the same item provider. Furthermore, in addition to fixed effects, the covariates include a progressive counter for each charity, which effectively controls for repeated sales by the same provider.

Common demand shocks can also introduce correlations across auctions, invalidating the instrument. For instance, when Charitystars and a provider set the q of an item, they may do so with the auction price of concurrent and past auctions in mind. Thus, concurrent auction outcomes could merely reflect past prices rather than Charitystars's actual preference over q. Yet, the correlation between q (reserve price) and the average prices of concurrent auctions is only 0.04 (0.06). There is also no correlation between the fraction donated and either the average price or the average number of bidders in the auctions concluded 10, 20 or 30 days prior to the end of that auction (Appendix Table C2).[12] Overall, these results indicate little to no cross-auction correlation, supporting the validity of the instruments.

In conclusion, bidders react to donations. The IV estimates using procurement outcomes across auctions within a five-day window as instruments for q and reserve prices are slightly larger than the OLS estimates, statistically different from zero, although less precise (cf. Table C3 in the online appendix). These estimates indicate that a 10% donation leads to an average price increase of 4.9%. Related papers have found similar results. For example, Elfenbein and McManus (2010) estimated that the prices of charitable eBay listings where the seller donates 10% are 6.6% larger than comparable non-charitable eBay listings.

Extensive margin. Bidder participation does not increase with the fraction donated (q). A total number of 2,361 users compete in an average of 4.66 different auctions. This average

[12] Auction prices do not increase with the level of competition in concurrent auctions. The average number of bids placed (β: –1.092, S.E.: 1.098) and the average number of bidders (β: 8.653 , S.E.: 6.152) participating in concurrent auctions ($\pm$5 days) do not explain the variation in an auction's price (R^2: 0.002).

increases to 7.73 after excluding bidders who bid on only one auction. Seventy percent (80%) of the bidders who place at least two (three) bids bid on a minimum of two auctions with different q. The raw data show no correlation between the number of bidders participating in an auction and its q (Spearman correlation: 0.088). The following Poisson regression examines the association between the fraction donated (q) and the number of bidders:

$$\log(\mathbb{E}[number\,of\,bidders_t|\mathbf{x}_t, q_t]) = \delta_0 + \mathbf{x}_t\delta + \delta_q q_t + \log(length_t) + \epsilon_t,$$

where q_t is the fraction donated and $\mathbf{x}_t$ is as in (3.1) and $length_t$ is the exposure variable and counts the days since the first bid in auction t. Table 2 reports the estimated coefficients which should be interpreted in terms of the number of bidders per day. The results confirm the absence of a correlation between q and the number of bidders, and are also confirmed by instrumenting q as previously done (Appendix Table C4).[13]

Table 2: Number of daily bidders per auction and fractions donated

Number of daily bidders	(I)	(II)	(III)	(IV)	(V)
Fraction donated (q)	0.049	0.066	0.020	0.045	0.020
	(0.060)	(0.061)	(0.061)	(0.061)	(0.064)
Main variables	✓	✓	✓	✓	✓
Add. charity dummies		✓	✓	✓	✓
League/match dummies			✓	✓	✓
Time dummies				✓	✓
Charity fixed effects					✓
Pseudo R-squared	0.124	0.126	0.137	0.149	0.173
BIC	5,909	5,929	5,977	6,025	6,128
N	1,107	1,107	1,107	1,107	1,107

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

Note: Poisson regression of the number of bidders on covariates. The exposure variable is the length of each auction. The control variables are defined in the online appendix. Robust standard errors in parenthesis.

Asymmetric bidding. Before turning to the auction model, let us consider potential asymmetries in terms of how bidders bid on an auction. Two main sources of asymmetries can be observed. First, bidders of different nationalities could employ different bidding strategies.

[13] Since bidders should entry earlier in auctions with lower starting prices, all else equal, interacting *length* with q might inform about differential entry based on q. Adding this variable to the covariates in Table 2 returns statistically and economically insignificant estimates, pointing to a limited role for differential entry.

However, Appendix Table C7 shows no effect of a winner's nationality on prices. Second, not all bidders may care equally about donations. Considering the case of collectors, i.e., bidders who won more auctions than the median winner, Appendix Table C8 shows that on average, recurrent winners do not behave differently from other bidders. Thus, the following sections introduce a model where symmetric bidders compete for winning an item and donating. The model is then estimated to learn Charitystars's demand elasticity.

3.2 Demand Model

This section extends 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. The model examines both the bidders' optimal strategy and the revenue-maximizing level of q.

The model measures the additional utility gained from donating to charity as $\beta \cdot q \cdot price$, where β transforms the funds raised ($q \cdot price$) in utils. Hence, β denotes the satisfaction gained from winning an auction and donating. Although losing bidders do not consume the item they bid on, thus receiving no consumption utility, they enjoy the fact that the awarded charity receives funding. The reward of the losing bidders is $\alpha \cdot q \cdot price$. As charitable motives cannot explain the full amount of a participant's bid, the literature assumes that $\alpha, \beta \in [0,1)$. Therefore, the utility to a bidder who values consuming the item v is

$$u(v;\alpha,\beta,q) = \begin{cases} v - price + \beta \cdot q \cdot price, & \text{if } i \text{ wins,} \\ \alpha \cdot q \cdot price, & \text{otherwise.} \end{cases} \tag{3.2}$$

Despite its simplicity, this utility specification encompasses the most common models of altruism based on the relative sizes of α and β, as summarized in Table C9 in the online appendix. If $\alpha = \beta = 0$, bidders are not altruistic and the classic textbook auction model applies. Bidders are purely altruistic when their utility does not depend on the identity of the donor, namely, when $\alpha = \beta > 0$ (as in Engelbrecht-Wiggans, 1994). In this case, bidders are motivated solely by their compassionate concern for the activities of the charity. In contrast, selfish motives are present when bidders take pride in donating (e.g., Andreoni, 1990). In this case, $\beta > \alpha$, implying that bidders receive a "warm glow" when winning and donating. An extreme case of "warm glow" exists when bidders only care about their donations and have no intrinsic motivations (if $\beta > \alpha = 0$). This model of altruism captures the role of social status or prestige in donations (e.g., Harbaugh, 1998).[14] Leszczyc and Rothkopf (2010) provide empirical evidence showing that $\alpha > \beta > 0$ using a field experiment.

[14]This model can also be used to study bidding when bidders receive subsidies (e.g., Athey *et al.*, 2013).

In such a "volunteer shill" model, bidders derive more utility from others' contributions than from their own. The next subsections show that these models of altruism shape market outcomes.

3.2.1 Equilibrium Bid in Charity Auctions

The optimal symmetric strategy is a function of the fraction donated (q), altruistic parameters (α, β) and valuations (v). The following regularity assumption is maintained throughout.

Assumption 1. *Regularity:*

1. *All $n > 1$ bidders have private and independent values for the auctioned item. These values are drawn from a continuous distribution $F(\cdot)$ with density $f(\cdot)$ on a compact support $[\underline{v}, \overline{v}]$;*

2. *The hazard rate of $F(\cdot)$ is increasing.*

The independent private value assumption is relaxed in the estimation by the inclusion of auction heterogeneity, which effectively allows for affiliated values. Alternatively, all the bidders could value a jersey equally but enjoy only imperfect signals of this value before bidding. Under such a common values scenario, the winner's curse increases in the number of bidders. As a result, bidders will shade their bids more as more bidders join an 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 game, which is important to identify the model primitives $\{F(v), \alpha, \beta\}$.

Ascending charity auctions, which are typical of online markets, are strategically equivalent to second-price charity auctions (Engers and McManus, 2007). The utility of a bidder with value v in a second-price auction where a fraction q of the price goes to a charity is:

$$\begin{aligned} \mathbb{E}[u(v;\alpha,\beta,q)] = & \underbrace{\mathbb{E}\left[v - (1-\beta\cdot q)\cdot price,\ i \text{ wins}\right]}_{i \text{ wins and pays } price} + \underbrace{\alpha\cdot q\cdot price\cdot \Pr\left(i\text{'s bid is } 2^{nd}\right)}_{i \text{ loses and bids } b_i = price} \\ & + \underbrace{\alpha\cdot q\cdot \mathbb{E}\left[price, i\text{'s bid is below } 2^{nd}\right]}_{i \text{ loses and } price > b_i}, \end{aligned} \tag{3.3}$$

where α and β are as defined in Equation 3.2 and *price* denotes the second-highest bid as this is the price at which the highest bidder wins the auction. The expected utility is composed of three mutually exclusive events. In the first event, the bidder wins the contest, pays the price, enjoys v and the additional utility gained from donating ($\beta \cdot q \cdot price$). In the second and third events, the bidder either drops out as the second-highest bidder or before. 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 this second-price charity auction, the equilibrium bid for a bidder with private value v and altruistic parameters (α, β) is (the derivations are in Online Appendix A.4):

$$b^*(v;\alpha,\beta,q) = \frac{1}{1+q\cdot(\alpha-\beta)}\left[v + \int_v^{\overline{v}} \left(\frac{1-F(x)}{1-F(v)}\right)^{\frac{1-q\cdot\beta}{q\cdot\alpha}+1} \mathrm{d}x\right]. \tag{3.4}$$

As the fraction donated approaches zero, the bid function collapses to a second-price noncharity auction. Therefore, the model includes the classic textbook second-price auction model as a special case. This bid function is also optimal in the context of ascending online auctions: at equilibrium, a bidder with the value of v drops out of the auction when $price \geq b(v;\alpha,\beta,q)$.

3.2.2 Comparative Statics

Does increasing the fraction donated necessarily increase bids? When $\alpha = 0$, Equation 3.4 collapses to $b^*(v;\alpha,\beta,q) = \frac{v}{1-q\cdot\beta}$, indicating that a larger fraction donated (q) is equivalent to a higher β. In this case, bids increase in q. More generally, whether bids increase or decrease in q depends on the relative values of α and β according to the following lemma.

Lemma 1. *Bids are*

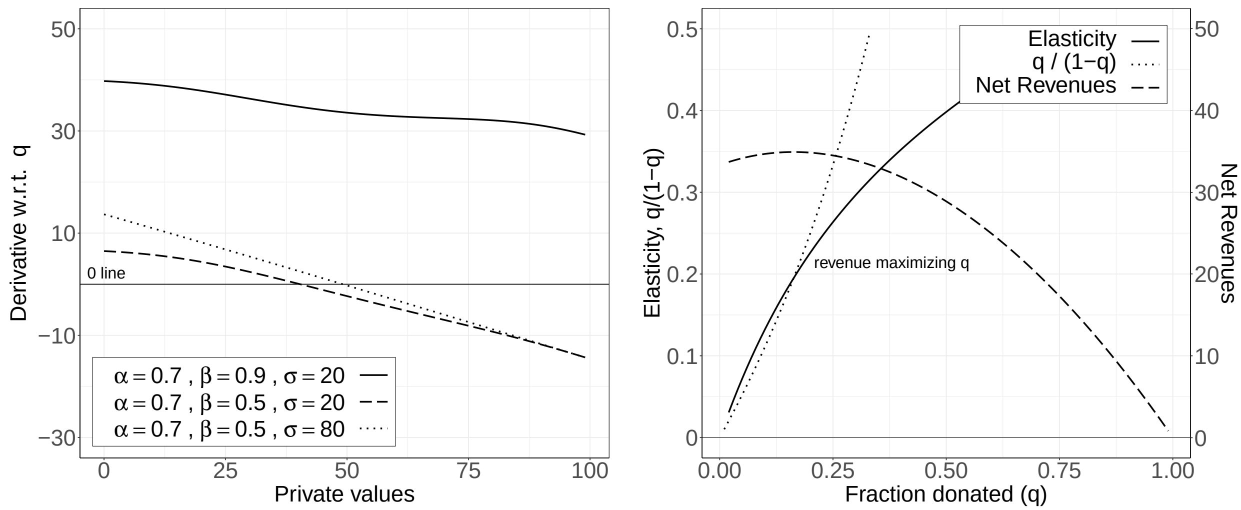
- *increasing in q if $\beta \geq \alpha$;*
- *decreasing in q in the interval $(\tilde{v}, \overline{v}]$, where $\tilde{v} \in [\underline{v}, \overline{v}]$, if $\alpha > \beta$.*

Proof. See Online Appendix A.2.

Panel (a) of Figure 2 provides graphical support to Lemma 1. The solid line ($\beta \geq \alpha$) shows that bidders revise their bids up if q increases due to "warm glow." The dotted and dashed lines instead refer to the derivative of the bid functions with respect to q under the "voluntary shill" model ($\beta < \alpha$): bids increase for bidders with low values and decrease for bidders with high values. Volunteer shill bidders balance the risk of winning the auction with the extra utility from driving up prices. The implications of this tradeoff differ based on a bidder's likelihood of winning the auction. A marginal change in q intensifies the degree of substitution between winning the auction and gaining from another bidder's contribution to charity, which leads high-value bidders to decrease their bids. By contrast, low-value bidders are unlikely to win; since they can affect their payoffs only when their bids rank second-highest, they increase their bids to extract surplus from the winner. Since the greater the variance of the distribution of values is, the more likely a bidder is to rank second-highest, more bidders with low private values will increase their bids when an auction is relatively uncertain (compare the dotted and dashed lines).

Figure 2: How the fraction donated affects bids and net revenues

(a) Derivative of the bid with respect to q (b) The net revenue-optimal donation (q_R)



Note: Panel a. This panel reports the analytical derivative of the bid function in Equation 3.4 with respect to q. In this simulation, $q = 0.85$ and $F(\cdot)$ is a truncated normal distribution in $[0,100]$ with mean 50 and standard deviation σ. Panel b. This panel shows the optimal fraction donated (q_R) is found intersecting the elasticity of the expected winning bid with respect to q and $q/(1-q)$. The 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) (i.e., the second-highest bid times $1-q$). The distribution of the private values $F(v)$ is uniform in $[0,100]$, $\alpha = 0.7$, $\beta = 0.9$ and there are two bidders.

3.2.3 Net Revenues

The firm should maximize net revenues if procurement costs are sunk. Intuitively, net revenues first increase as the auctioneer increases the fraction donated (q), then they reach a maximum before decreasing to zero when $q = 1$, in which case the auctioneer donates all the proceeds.

Proposition 1. *The net revenue-optimal fraction donated q^R*

- *solves $\eta(p^e(q_R), q_R) = \frac{q_R}{1-q_R}$ for $\alpha > 0$, where $\eta(p^e, q) = \frac{\partial p^e}{\partial q}\frac{q}{p^e}$ is the elasticity of the expected price, p^e, to the fraction donated, q;*
- *is equal to 0 when $\alpha = 0$.*

Proof. See Appendix A.3.

When α is positive, net revenues have an inverted-U shape, which is maximized at q_R – the level where the marginal benefit from higher bids, $(1-q)\eta$, equates the marginal cost from donating an extra euro, q. Panel (b) of Figure 2 depicts revenues from auctions with different q and shows that net revenues (right axis) are optimized at the fraction donated where $\eta = q/(1-q)$. If $\alpha = 0$ the bid function becomes $b^*(v;\alpha,\beta,q) = \frac{v}{1-q\cdot\beta}$, and an increase in q does not increase net revenues to the auctioneer because each $q \cdot \beta$ dollar increase in price costs the auctioneer q dollars. Since $\beta \in [0,1)$, a revenue-maximizing auctioneer should not donate if bidders are indifferent to the donations of other bidders.

The role that externalities play in charity auctions is not clear in the empirical literature. For instance, Leszczyc and Rothkopf (2010) attribute the widespread overbidding in their experimental charity auctions (over noncharity auctions) to significant externalities. However, their conclusion that revenues are higher when $\alpha > \beta$ is true only if few high-value bidders shade their bids in charity auctions. In their data, this seems to be the case, as their auctions averaged fewer than four bidders; thus, low-value bidders have high chances of ranking second and setting the price.[15] In conclusion, preferences play a central role in determining auction outcomes. Thus, their identification is crucial for estimating the elasticity of demand.

3.3 Nonparametric Identification of the Demand Model

As discussed in a previous section, the observation that transaction prices in different auctions are close despite having different fractions donated may be the result of bid shading by the high-value bidders of the auctions where the fractions donated are higher. Therefore, it is important to identify the primitives of the model, namely, $\{F(v), \alpha, \beta\}$, in order to assess the pass-through of donations to consumers' willingness-to-pay. This section first presents the identification argument assuming that all bidders constantly monitor the auction. This assumption is then relaxed to allow for non-truthful bidding as bidders in an online ascending auction may not continuosly update their bids.

Truthful bidding. The identification is based on the first-order conditions of the problem in (3.3), and it relies on variations in the fraction donated across otherwise identical auctions and on the monotonicity of the bid function 3.4. If all the bidders bid truthfully, as is optimal in second-price auctions, and all the bids are observed, the bid distribution $(G(b;q))$ and its inverse hazard rate $(\lambda_G(b;q))$ can be estimated directly from the data. Since bids are

[15] In a related field experiment, Carpenter *et al.* (2008) show that, for some auctioned items, bidders bid below their reported willingness to pay and corresponding store prices. This result is compatible with significant externalities across bidders, although their experiment is not designed to bring evidence on that point. A similar outcome is also obtained if charity auctions attract less bidders than similar non-charity auctions (e.g., Carpenter *et al.*, 2010, Haruvy and Popkowski Leszczyc, 2018).

invertible functions of private values, the bid distribution is equal to the private values distribution ($F(\cdot)$). This equivalence allows the FOC of a bidder with value v bidding $b = b(v;\alpha,\beta,q)$ to be rewritten as follows:[16]

$$v = (1 - \beta \cdot q) \cdot b + \alpha \cdot q \cdot \big(b - \lambda_G(b;q)\big). \tag{3.5}$$

This equation shows that a bidder's private value is equal to the price she pays net of the benefit she receives by donating ($\beta \cdot q \cdot b$), plus a term that measures the surplus that can be extracted from her (a sort of virtual valuation). b and q are data, and $\{v,\alpha,\beta\}$ are unknown.

The right-hand side of Equation 3.5 is strictly increasing and differentiable in the vector of bids, implying that no two different combinations of $\{\alpha, \beta\}$ yield the same vector of private values, and that every distribution $F(.|\tilde{\alpha},\tilde{\beta},q)$ is unique according to Theorem 1 in Guerre *et al.* (2000) given $\{\tilde{\alpha},\tilde{\beta}\}$ and the data.[17] Thus, observing two sets of auctions, e.g., A and B, with different fractions donated, $q_A \neq q_B$, but same private value distributions for all their bidders identifies α and β, because the relation $F(v;\alpha_0,\beta_0,q_A) = F(v;\alpha_0,\beta_0,q_B)$ is valid only if $\{\alpha_0,\beta_0\}$ are the true parameters. Then, plugging $\{\alpha_0,\beta_0\}$ in equation 3.5 identifies $F(v)$. This identification strategy relies on the following testable assumption:

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

This identification strategy could fail if, for example, bidders' private values are greater for auctions with higher q, such that $v(q)$ is an unknown increasing function of q (e.g., sorting). In this case, $F(v(q_A);\alpha_0,\beta_0,q_A) \neq F(v(q_B);\alpha_0,\beta_0,q_B)$, and α and β are not nonparametrically identified. The theoretical model in Section 3.2 satisfies Assumption 2 because it defines $F(\cdot)$ as the unconditional private value distribution of bidders within an auction, but it places no restriction across auctions. Thus, Assumption 2 is testable using auctions with $q \neq (q^A,q^B)$.[18] In support of this assumption, Section 3.1 shows that Charitystars's bidders join multiple auctions without regard for q and that there is no correlation between the number of bidders, other auction characteristics, and q.

Online auctions. In online auctions, not all bidders bid according to the first-order condition of the problem in (3.3). First, a bidder may place a low starting bid but then forget to update her bid. Second, in equilibrium, the winner pays the price at which the second-highest bidder quits, which suggests that not even the winning bidder bids according to the bid

[16] Under Assumption 1, $G(B) = Pr(b(v) < B) = Pr(v < b^{-1}(B)) = F(b^{-1}(B))$. Therefore, $G(b) = F(v)$ and $g(b)\,b' = f(v)$.

[17] Theorem 1 of Guerre *et al.* (2000) relies on the same regularity conditions presented in Assumption 1.

[18] After the model is estimated in Section 3.4, Assumption 2 is tested and not rejected using out-of-sample data. This identification strategy is related to that of risk aversion in first-price auctions, which 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).

function (3.4). Therefore, Equation 3.5 cannot be used for identification because a one-to-one mapping between the distributions of values and the observed bids does not exist.

To draw the mapping between the distributions of bids and private values, recall that an online auction ends when the second-highest bidder drops out. As a result, the second-highest bidder solves Equation 3.5 and his or her bid is equal to the winning bid. Because almost half of Charitystars's auctions extend beyond their allotted time due to a bid in the last four minutes, the intense competition across high-value bidders towards the end of the auction and the negligible bid increase support the thesis that the last bid indeed reflects the valuation of the second-highest bidder. Thus, in equilibrium, the distribution of winning bids, $G_w(b;q)$, is equal to the distribution of the second-highest bids, which is a known invertible function of the underlying unknown distribution of bids, $G(b;q)$, given the number of bidders, n. $G(b;q)$ is identified by inverting this mapping – i.e., $G_w(b;q) = G(b;q)^{n-1} + (n-1) \cdot (1 - G(b;q)) \cdot G(b;q)^{n-2}$. Under Assumption 1, the recovered distribution of bids is equal to the distribution of private values because the second-highest bidder also has the second-highest valuation, implying that $G(b;q) = F(v)$. This information, in turn, allows the identification of α, β and $F(v)$ through Equation 3.5 and Assumption 2.

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., $q \in \{q_1, q_2, ..., q_K\}$), as shown in Corollary 1 in Appendix A.5. This proof uses the panel structure of the data to create a projection matrix that cancels out the left-hand side of Equation 3.5 to identify α and β as indicated in Proposition 2.

3.4 Estimation of the Demand Model

The primitives of the model $\{F(v), \alpha, \beta\}$ are estimated by comparing bids in auctions with different fractions donated (q). The estimation is based on auctions where $q \in \{10\%, 85\%\}$, which are among the most frequent in the dataset. The first step of the estimation procedure accounts for auction heterogeneity. The second step determines the bid distributions and constructs the moment conditions. The last step estimates the primitives according to the method of moments.

First step. Auction heterogeneity is accounted for through a flexible regression of the log of transaction prices on listing, item and charity characteristics as follows:

$$\log(price_t) = \gamma_0 + \mathbf{x}_t \gamma + w_t, \tag{3.6}$$

where t indexes the auctions. The vector $\mathbf{x}_t$ includes all the variables in Column 1 of Table 1 except for q. An alternative approach would be to subset the data to compare outcomes in auctions with different q but the same number of bidders, thereby excluding the variable $number\,of\,bidders$ from $\mathbf{x}_t$ (cf. Lu and Perrigne, 2008). However, pooling the data has two main advantages. First, it improves inference because, given the size of the dataset, some subsets might have too few observations. Second, it provides a single $\{\hat{\alpha}, \hat{\beta}, \hat{F}(\cdot)\}$ estimate rather than one such triple for each number of bidders, simplifying the counterfactuals.[19] Then, the regression residuals ($\hat{w}_t$) are the pseudo winning bids from homogeneous auctions (e.g., Haile *et al.*, 2003) and are a function of α, β, q and the winners' private values.[20]

Second step. The bid distribution and density are necessary elements of (3.5). The identification argument requires that $\hat{w}_t$ is grouped based on q to determine the two distributions of bids, namely, $\hat{G}^q(\cdot)$ with $q \in \{0.1, 0.85\}$, from the empirical distributions of winning bids, namely, $\hat{G}^q_w(\cdot)$. The densities $\hat{g}^q(\cdot)$ are computed analogously. The empirical CDF and pdf of $\hat{w}_t$ are computed with a Gaussian kernel with bandwidths following Li *et al.* (2002).

Third step. The resulting two sets of FOCs are then matched along the quantiles of the distributions of bids, i.e., two bids $b^{0.1}$ and $b^{0.85}$ are matched if $\hat{G}(b^{0.1}; q = 0.1) = \hat{G}(b^{0.85}; q = 0.85)$. As a result, the left-hand side of (3.5), $\hat{v}^q$, is equal to its matched counterpart at the true values $\{\alpha_0, \beta_0\}$, meaning that the relation $\hat{v}^{0.1}_\tau(\alpha_0, \beta_0) = \hat{v}^{0.85}_\tau(\alpha_0, \beta_0)$ holds for each τ-quantile of the distribution of values. Thus, the criterion function is as follows:

$$\min_{\{\alpha,\beta\}} \frac{1}{T} \sum_{\tau}^{T} \left(\hat{v}^{0.1}_\tau(\alpha, \beta) \;-\; \hat{v}^{0.85}_\tau(\alpha, \beta)\right)^2, \tag{3.7}$$

where T is the number of observations. The distribution of private values $\hat{F}(\cdot)$ is the empirical distribution of the left-hand side of Equation 3.5 after $\{\hat{\alpha}, \hat{\beta}\}$ are plugged in.[21]

[19] The nonparametric approach effectively postpones the aggregation problem to the counterfactual stage. Section 3.4.1 performs the non-parametric approach on subsamples with similar number of bidders and returns α, β estimates that are in line with those obtained including the number of bidders as a control in (3.6).

[20] Roberts (2013) shows that the reserve price is an adequate control for unobservables if the effect of unobservable factors is monotonic in the reserve price. Recently, Freyberger and Larsen (2017) extended existing deconvolution methods (Krasnokutskaya, 2011) to account for unobserved heterogeneity in English auctions (see also Decarolis, 2018). These approaches decompose winning bids and reserve prices into an auction-specific random term and bid- and reserve price-specific idiosyncratic random terms. If these three terms are independent, their distributions can be recovered nonparametrically. However, this independence assumption is violated in the Charitystars setting because bids and reserve prices depend nonlinearly on the fraction donated, which invalidates the use of deconvolution techniques.

[21] Online Appendix F studies the properties of this estimator. In particular, it shows that the identification fails if the fractions donated in the two auctions are very close, and presents simulations suggesting that the

3.4.1 Estimation Results and Model Fit

Table 3 reports the estimation results. The identification requires a constant number of potential bidders, n, to perform the inversion in the second step. n is set to the 99$^{\text{th}}$ percentile of the distribution of bidders in the first row of the table to avoid outliers. Consistent with other studies (e.g., DellaVigna *et al.*, 2012, Huck *et al.*, 2015), the results provide evidence of "warm glow" agents ($\hat{\beta} > \hat{\alpha} > 0$); such individuals derive more utility from their own donations than from those of other bidders. The table also reports estimates for other values of n in rows two to five that are similar to the main estimates and always significant – bootstrapped 95% confidence interval are in square brackets. The remaining part of this section discusses the fit of the model.

Table 3: Estimated altruistic demand parameters

Number of bidders Quantile	n	α [95% CI]	β [95% CI]
99%	16	0.227	0.490
		[0.132, 0.321]	[0.255, 0.650]
95%	14	0.224	0.490
		[0.130, 0.317]	[0.255, 0.650]
90%	12	0.220	0.489
		[0.220, 0.128]	[0.255, 0.648]
75%	10	0.215	0.488
		[0.215, 0.124]	[0.255, 0.647]
50%	7	0.202	0.485
		[0.202,0.116]	[0.255, 0.644]

Note: The results of 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 stemming from other individuals' donations and the bidder's own donations, respectively. 95% bootstrap confidence intervals are in square brackets (401 repetitions). The dataset includes only auctions where $q \in \{10\%, 85\%\}$.

Expected revenues. Simulated prices are computed by plugging the estimated primitives $\{\hat{F}(v), \hat{\alpha}, \hat{\beta}\}$ into Equation 3.4 and integrating with respect to the density of the second-highest bid. To test the model predictions, Appendix Figure D7 first computes the simulated prices for $q \in \{10\%, 85\%\}$ and for each value of the number of bidders within its interquartile range (between 5 and 10), and then compares them with the corresponding observed average prices.[22] The Figure shows that the modal deviation is approximately 5% in magnitude for both $q = 0.10$ (black bars) and $q = 0.85$ (white bars). The note under Appendix Figure

estimator performs well even in small samples, it is consistent and asymptotically normal.

[22] All prices are translated into euros by exponentiating the sum of the expected price in utils with the relevant heterogeneity level. For example, when simulating the prices of auctions with $q = 0.85$ and 7 bidders, the algorithm adds the average fitted values in Equation 3.6 from this subset.

D7 reports the p-values of the differences between the average observed prices and the average simulated prices. These differences are never statistically significant. For simplicity, the following analyses consider the heterogeneity level of the median fitted values in (3.6), while Appendix E.3 shows that all the following results are robust to varying levels of heterogeneity.[23]

Test of identification. The estimation procedure relies on Assumption 2, which states that $F(\cdot)$ does not depend on q, implying that bidders do not sort across auctions with different q based on their private values. Therefore, individuals who bid on auctions where $q \notin \{0.10, 0.85\}$ should bid according to the same primitives as those who bid on the in-sample auctions. A direct test of this assumption exploits the monotonicity of the FOCs by applying both the estimated coefficients in the first step and the estimated $\hat{\alpha}$ and $\hat{\beta}$ on the out-of-sample data. The identification strategy fails if the implied distribution of values differs from that estimated in-sample, $\hat{F}(\cdot)$. Exploiting the auctions with $q = 0.78$, Figure 3 compares the counterfactual density of private values computed on these auctions (dotted line) with the in-sample estimated density (solid line). The two pdfs have similar shapes and the Kolmogorov-Smirnov test does not reject the null hypothesis of equality at the 0.845 level. This test is conservative as the auction heterogeneity in the first-step regression could differ across the samples.[24]

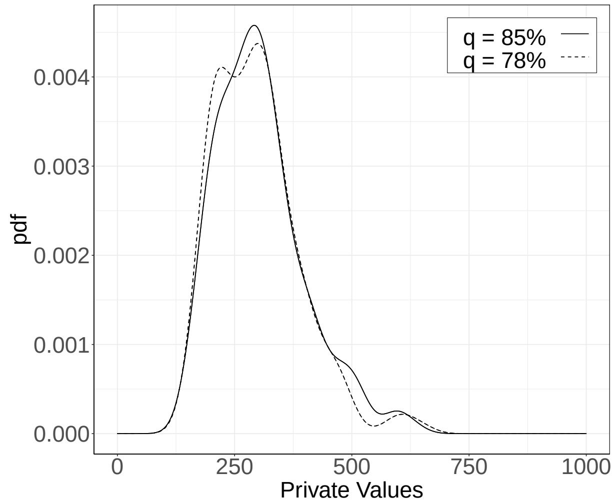
Over-identification. The assumption of symmetric bidding helps to keep the theoretical model tractable at the cost of some flexibility.[25] To test whether higher-value bidders have different altruistic preferences than low-value bidders, the model is estimated again after grouping the moments in Equation 3.7 based on whether they refer to quantiles above or below the median private value. Therefore, this approach tests for a correlation between the altruistic parameters and the private values. The online appendix reports the test statistics of the difference across the densities estimated on these subsamples (Figure D10); the null hypothesis that each pdf is equal to the pdf in the main estimation is never rejected,

[23]The online appendix also investigates the shape of the bid function with respect to q using quantile regressions (Appendix Table C1 and Figure D4): the results indicate a log-linear relation between prices and q. Given the structural estimates, the ANOVA tests presented in Panel (b) of Figure D10 do not reject the null hypothesis that simulated bids are log-linear in q.

[24]The test, presented in Figure D8 in the online appendix, shows that the null hypothesis cannot be rejected also for auctions with $q \in \{0.72, 0.80\}$. To determine how restrictive is the inclusion of the number of bidders in (3.6), the out-of-sample test algorithm is performed on subsamples of auctions with 5 and 6, 6 and 7, 7 and 8, or 8 and 9 bidders. The altruistic parameters estimated on these subsamples are consistent with those in Table 3, and the out-of-sample tests never reject the null hypothesis. Figure D9 in the online appendix provides further information. Thus, the results from not including the number of bidders in the first-step of the estimation algorithm are consistent with the main estimates.

[25]A simple test of asymmetric bidding is to compare the densities of pseudo-winning bids from (3.6) across auctions won by recurrent and non-recurrent winners. The test results are reported in the online appendix (Figure D6). The failure to reject the null hypothesis undermines asymmetric bidding as a first-order problem.

Figure 3: Out-of-sample validation



Note: Comparison of the densities of the private values estimated from the structural model employing data from auctions with $q = \{0.10, 0.85\}$ and the density of the private values obtained by projecting the three-step estimation procedure to the $q = 0.78$ auctions. The null hypothesis (equality) cannot be rejected at the standard level (p-value: 0.845). The estimation of the bid distributions assume that $n = 16$ and use a Gaussian kernel and Silverman's rule-of-thumb bandwidth (Silverman, 1986).

suggesting that the assumption of symmetric bidding is not overly restrictive.

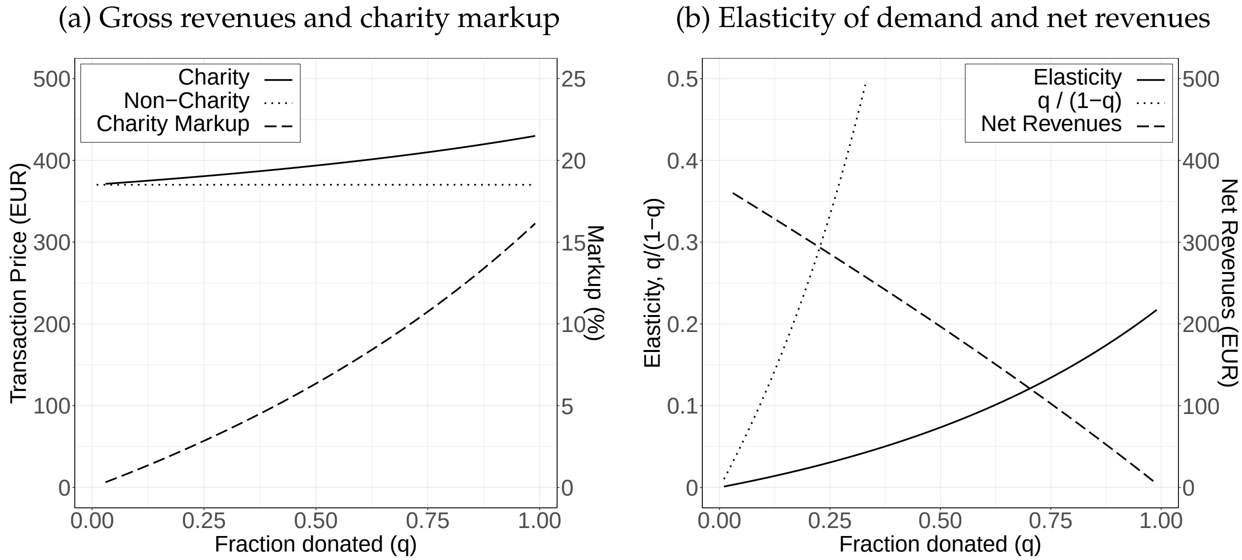
Instrumental variables. The simultaneous determination of an auction's reserve price and the fraction donated may create endogeneity concerns. Following the discussion on instrumental variables in Section 3.1, the reserve price is instrumented with the average reserve price and the average auction length across all the other auctions ending within five days of the focal auction. Estimates are reported in the online appendix (Table C11), which shows little change in the estimated $\hat{\alpha}$ and $\hat{\beta}$.

3.4.2 Is There a Charity Premium?

This section explores the existence of a charity mark-up and the revenue-optimal fraction donated. A short discussion generalizes the results.

Charity premium. The existence of a charity premium comes with no surprise since bidders have warm-glow preferences. As a result, the distribution of bids stochastically dominates the distribution of private values, as shown in Figure D11 of the online appendix. Therefore, the expected transaction price is larger than the expected second-highest private value. Their difference – the charity mark-up – is plotted in Panel (a) of Figure 4 (dashed line, right axis): the markup increases in q and reaches a maximum of 15%. This value is close to the estimates in Haruvy and Popkowski Leszczyc (2018), who find a 14% premium in

Figure 4: Charity premium



Note: Panel a. This panel displays the expected gross revenues at the estimated primitives (solid line), the revenues from a similar second-price noncharity auction (dotted line), and the charity markup (dashed line, right axis). Panel b. This panel 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 computations assume cubic spline approximations for the density $f(v)$ and the distribution $F(v)$ and that the number of potential bidders is the average observed number in both panels.

charity versus non-charity auctions using experimental data, and to Elfenbein and McManus (2010), who find a 12% premium when the eBay auctioneers donate 100% of their sale prices. The charity premium is instead close to zero when the fraction donated is small. These observations indicate a rather inelastic demand for donations.

Maximizing revenues. Proposition 1 states that the revenue-maximizing fraction donated is found at the intersection of the elasticity curve and $q/(1-q)$. From Panel (b) of Figure 4, these two curves intersect only at $q = 0$: net revenues are greater than €300 when the firm does not donate, and constantly decrease as q increases (dashed line, right axis). As a result, Charitystars can increase its net revenues by €250 on average by holding standard auctions.

Discussion. Despite the charity premium, the price increase does not compensate for the amount donated. Due to the salience of Charitystars's donations for consumers, this result could matter for charity-linked products more broadly (e.g., Arora and Henderson, 2007), as cause-related marketing campaigns often display small donations. For instance, donations to Product Red, a large charity fighting HIV that fundraises by keeping a fraction of the price of items sold by large partnering corporations (e.g., Apple), are generally less than 10% of the corresponding item price. Similarly, Tom Shoes, a shoe company that used to donate a pair of shoes for each pair sold, has recently reverted to a much more flexible $1 donation for every $3 in sales, as consumer demand proved to be insufficiently elastic to sustain the previous one-for-one donation scheme (TOMS, 2019, p. 69). This view is also consistent with experimental evidence from the cause-related marketing literature showing decreasing marginal returns to donations (Koschate-Fischer *et al.*, 2012).

The demand results also inform a growing literature on participative pricing. In a recent experiment, Gneezy *et al.* (2010) investigate the willingness to pay for a photograph immediately after riding a roller coaster–like attraction in a US amusement park. The authors compare two strategies: a fixed posted price (no donation) and a pay-as-you-want plus a 50% donation scheme and show that the profits-per-ride net of donations are non-statistically different across the treatments. To the extent that the pay-as-you want plus a 50% donation scheme is similar to bidding in charity auctions (with $q = 0.5$), their findings confirm that consumers do not substantially increase their willingness to pay due to a donation even in markets different from auctions.

In conclusion, the demand analysis suggests that consumers are unlikely to be a driver of firms' prosocial behaviors. To address why Charitystars donates and to identify its welfare implications, the next section explores how donations impact the firm's marginal costs.

4 Supply: Donations and Procurement Costs

Charitystars's donations would be profitable if its procurement costs decreased as the fraction donated increased. This section reports empirical evidence of bargaining between Charitystars and the item providers, which was also confirmed through conversations with advisors of the firm before modeling and estimating the cost of procuring an item.

Evidence of bargaining. The pause in the leading European football competitions during the summer months provides an opportunity to illustrate the bargaining process. In July and August, the auctionable items become scarcer, which could strengthen the negotiation positions of the item providers. The raw data indicate that the average fraction donated (q) during the summer months is 0.078 larger than in the other months (two-sided Welch t-test p-value: 0.001), which is a value greater than 10% of the average q. Auction, jersey, and charity heterogeneity is controlled in the following regression equation:

$$q_t = \gamma_0 + \mathbf{x}_t \gamma + \gamma_m \, summer\, month_t + u_t,$$

where $summer\, month_t$ refers to either August or to both July and August. Table 4 confirms that the average fraction donated by Charitystars is greater in the summer, suggesting a change in its bargaining power and thus in its negotiations with the item providers.[26]

Table 4: Evidence of bargaining

Fraction donated (q)	(I)	(II)	(III)	(IV)
August	0.100***	0.114***		
	(0.033)	(0.032)		
July & August			0.065***	0.051**
			(0.023)	(0.025)
Main variables	✓	✓	✓	✓
Add. charity dummies		✓		✓
League/match dummies		✓		✓
Charity fixed effects		✓		✓
Adjusted R-squared	0.346	0.477	0.347	0.476
N	1,107	1,107	1,107	1,107

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

Note: This table displays estimates from OLS regressions of the fraction donated on covariates. The top panel reports the coefficients of the dummy variables August (1 if the month is August and 0 otherwise) and July & August (1 if the month is either July or August and 0 otherwise). All the regressions include the reserve price, the number of bidders, and the number of bids placed; the remaining control variables are defined in the online appendix. Robust standard errors in parentheses.

Estimation of procurement costs. Regarding the optimal fraction donated, consider the decision of a profit-maximizing auctioneer whose revenues and costs vary with the fraction donated. Given the number of bidders, α, β and $F(\cdot)$, the auctioneer's problem is as follows:

$$\max_{q \in [0,1]} (1-q) \cdot \int_v b(v, \alpha, \beta, q) \, \mathrm{d}F_{(n)}^{(2)}(v) - c(q), \tag{4.1}$$

where $F_{(n)}^{(2)}(v)$ is the distribution of the second-highest private value out of n bidders. Denoting the expected price by p^e and its elasticity to the donation by η, the optimal donation, q^*, sets a change in costs due to a marginal increase in q equal to the relative change in net revenues as described by:

$$c'(q^*) = \frac{1-q^*}{q^*} \cdot \eta \cdot p^e(q^*) - p^e(q^*). \tag{4.2}$$

[26]Charitystars could donate more in the summer to induce more bidders to bid during periods when its website may have less traction. To solve this potential endogeneity concern, Table C5 in the online appendix instruments the reserve price and the number of bidders with the means of these variables for auctions ending within five days of the focal auction. The IV estimates of γ_m are larger than the OLS estimates, supporting the negotiation thesis. The note under the table reports the results of the diagnostic tests.

A comparison of the net revenue-maximizing donation from Proposition 1, q_R, and the profit optimal donation, q^*, implies that $q^* > q_R$ if $c'(q) < 0$. The demand estimates in Figure 4b imply that $q^R = 0$. Thus, the firm should donate only if its costs decrease in q.

Online Appendix A.6 extends the monopolist problem in (4.1) to the case where the firm and the item provider negotiate over the fraction donated within a Nash bargaining framework. The model's first-order conditions can be rewritten to yield an equation similar to Equation 4.2, where $c'(q)$ is a function of the bargaining weights; importantly, the section shows that bargaining implies that $c'(\cdot) \leq 0$. Therefore, while the monopolist framework is a simpler representation of the underlying environment, it is more flexible than the bargaining problem, as it does not restrict the sign of $c'(\cdot)$, which is ultimately an empirical question.

To avoid losses, Charitystars ensures that the smallest potential net revenue from a sale covers its corresponding procurement cost. Thus, the firm sets its reserve prices such that $(1-q) \cdot \textit{reserve price} = c(q)$. This information facilitates the estimation of the average marginal cost. The first step of this process consists of homogenizing the reserve prices by regressing them on the covariates previously used in the demand model:

$$\log(\textit{reserve price}_t) = \mathbf{x}_t \gamma + \xi_t, \tag{4.3}$$

where t indexes each one of the 1,107 auctions in the dataset (including all auctions where $q \leq 0.85$). Second, the homogenized reserve prices, r_t, are recomputed in terms of the median auction (as in Section 3.4.2) by exponentiating the sum of the residual and the median of the fitted dependent variable from Equation 4.3. Third, the costs are equal to the net homogenized reserve price, $c_t = (1-q) \cdot r_t$. Finally, the marginal costs are estimated by regressing c_t on a polynomial expansion of q (i.e., $\sum_{j=0}^{J} \pi_j q_t^j$).

In equation 4.3, including the $\textit{number of total bids placed}$ is helpful in terms of accounting for unobservable heterogeneity for two main reasons. First, if the firm sets a reserve price above an item's cost to discourage low-value bidders due to certain attributes that are not accounted for in $\mathbf{x}_t$ but that are observable to the bidders, the change in competition within the auction will be reflected in the number of bids placed, all else equal. Second, the auctioneer cannot directly affect this variable because it is realized at the end of the auction and after the bargaining stage. Hence, this variable effectively controls for a situation where the reserve price does not perfectly reflect procurement costs.

Table 5 displays the estimated coefficients using either a quadratic or a cubic functional form for costs. The estimated intercepts (π_0) and linear coefficients (π_1) are similar across the columns, while the introduction of the cubic term (π_3) inflates the quadratic coefficient (π_2) in the second column, and the standard errors in Column 2. This effect is due to the small number of auctions with q in the neighborhood of 50%.[27] Nevertheless, both specifications seem to fit the data reasonably well as they explain a large portion of the variance of the net reserve price.

Table 5: Cost estimation

Costs:	(I) Quadratic	(II) Cubic
π_0 (constant term)	240.38***	249.94***
	(13.93)	(74.23)
π_1 (linear term)	−453.91***	−570.77
	(69.01)	(864.43)
π_2 (quadratic term)	238.90***	495.01
	(66.98)	(1,824.09)
π_3 (cubic term)		−155.45
		(1,070.35)
Adjusted R-squared	0.589	0.588
BIC	11,909	11,916
N	1,106	1,106

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

Note: 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 refer to the linear (q), quadratic (q^2) and cubic (q^3) terms. Robust standard errors in parentheses.

From an inspection of the estimated marginal cost coefficients in the first column of Table 5, it can be observed that the linear term (π_1) is negative, while the quadratic term is positive (π_2). Therefore, for at least a portion of the support of q, procurement costs are decreasing in the fraction donated as $c'(q) < 0$. This result is consistent with the existence of bargaining between the firm and the item providers, and supports the thesis that the firm can purchase items at lower costs when it agrees to donate larger fractions of its sales.

The next section investigates the profitability of donating by comparing Charitystars's marginal costs and marginal revenues and presents several robustness exercises. The results shed light on Charitystars's objectives and their welfare consequences.

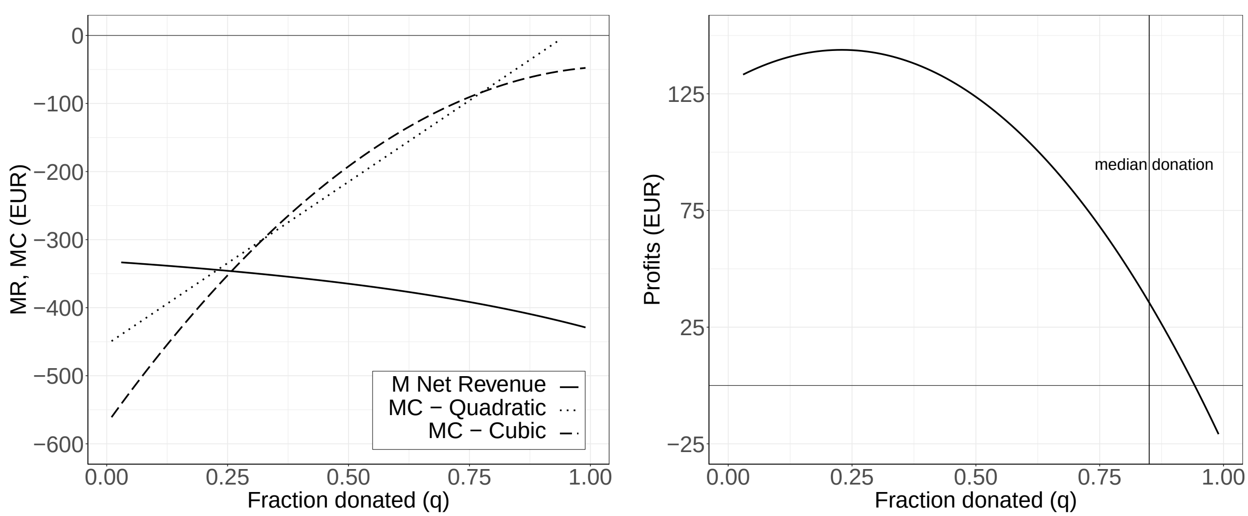
[27] The lack of observations with mid-range qs is due to a simple heuristic approach to negotiations: charities either receive a large percentage of the sale as a donation and a small upfront payment or vice versa.

5 Objectives and Welfare

This section uses the demand and supply estimates to study Charitystars's behavior and its implications for welfare. Maximizing profits means that the firm donates a fraction of its revenues that equates its marginal costs and net marginal revenues, as shown in (4.2). Panel (a) of Figure 5 plots these curves as a function of the fraction donated (q): despite the negative marginal revenues estimates (solid line), both marginal cost estimates are also negative for all q, with cost gains displaying diminishing marginal returns. Donations are profitable and profits are maximized by setting $q^* \simeq 0.25$, on average.[28] However, Charitystars donates well beyond q^* on average, which results in a substantial profitable deviation. The median (average) fraction kept by Charitystars is only 15% (30%) of the price, which yield expected profits of approximately €35 (€82) per auction. Panel (b) of Figure 5 shows that profits would jump to €144 at q^*. The next subsections consider the motives behind this strategy.

Figure 5: Profit-maximizing donation

(a) Marginal net revenues and marginal costs   (b) Profits per listing



Note: Panel a. The optimal fraction donated is found at the intersection of marginal costs (dotted and dashed lines) and marginal net revenues (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) or cubic polynomials (dashed line). Panel b. The expected profits at different fractions donated. The vertical line at 0.85 indicates the median donation in the data. Profits are computed using the quadratic cost case. The computations assume cubic spline approximations for the density $f(v)$ and the distribution $F(v)$ and that the number of potential bidders is the average observed number in both panels.

Omitted variables. The reserve price and the fraction donated are equilibrium outcomes that can be affected by unobservable variables. For instance, the firm's cost estimates may

[28] The optimal fraction donated is 0.23 in the quadratic cost case with bootstrapped 95% C.I. and 401 repetitions of [0.18, 0.29]. Similarly, it is 0.26 with 95% C.I. of [0.23, 0.30] for the cubic cost case.

not be reliable if it systematically sets higher reserve prices due to certain item attributes that neither bidders nor the econometrician observe. To account for such unobservables, the reserve prices in the first step of the demand model and the fractions donated in the third step of the supply model are instrumented using outcomes from concurrent auctions, as is done in Section 3.1. Online Appendix E.2 provides a complete discussion of the IV approach, including test results. Counterfactual simulations confirm that the optimal fraction donated is lower than that observed in the data, $q^* = 0.31$ (95% C.I. [0.29,0.36]), implying an even higher profitable deviation of €155 on average.[29]

Different bargaining powers. The firm's high donations could also depend on heterogeneity in the bargaining powers of different providers. Focusing on provider types, Online Appendix E.4 replicates the supply analysis on a subset of the auctions where the item providers are mentioned in the text of the auction listings (667 auctions). Among these auctions, the provider is either a charity (352 auctions) or a football personality or organization (315 auctions). Despite the small sample, the analysis finds that the the optimal average donation is similar to that in the main text for these provider types. These results support the idea that Charitystars bargains similarly with all item providers, who can either receive a large upfront price or a large portion of the auction price.

Reputation. Reputation is a broad term that encompasses several aspects of a business, and it is unrealistic to discuss all of its dimensions quantitatively. However, two payoff-relevant sources of reputation can be studied with this dataset: whether better reputation through high fractions donated correlates with more bidders and more auctions over time – the two sides of its market. To incorporate this time effect, the dataset is extended to all soccer jersey auctions before November 2018 through the following specification:

$$y_k = \rho_0 + \rho_1 \cdot y_{w-1} + \sum_{l=0}^{L} \tilde{\rho}_l \cdot \bar{q}_{k-l} + FE_{m(k)} + FE_{y(k)} + e_k,$$

which regresses a statistic of interest in week k, y_k, (e.g., average number of bidders) over its lag in the previous week, the average fraction donated during the current and past L weeks, $\bar{q}_{k-l}$, and month and year fixed effects. The estimated coefficients, reported in Table C12 in the online appendix, indicate a small, nonsignificant correlation between the average number of auctions (y_k) and both the average current and past q. Replacing y_k in the above regression with the average, the median, or the 9$^{\text{th}}$ decile of the distribution of the number of bidders in week k points to no associations between these variables and past donations

[29]The results are also robust to the inclusion of more covariates in both the demand and supply models and to levels of auction heterogeneity other than the median one. The online appendix reports these analyses in sections E.1 and E.3, respectively.

(Table C13 in the same appendix section). This result is consistent with Section 3.1, which finds a limited impact of q on the extensive margin of bidding. Therefore, the data reject the possibility of high donations to promote the two sides of the market.

Competition. Charitystars is a de facto monopolist in the e-commerce of footballers' memorabilia due to the large number and variety of auctions it offers.[30] There are also considerable barriers to entering in Charitystars's business due to the need for a sizable network of contacts that includes celebrities, and a large number of users.

Beliefs. It is unlikely that the managers of the firm believe that the demand they face is very elastic to the fraction donated because naively regressing prices on the fraction donated suggests that prices increase by only €6 – 9, when q increases by 0.1 (cf. Table 1).

Multiple purchases. Charitystars could make large donations to draw users to other products, such as paintings or dinners with celebrities. However, conversations with shareholders and advisors of the firm reveal that most of the users have a particular interest in soccer jerseys and that bidders do not bid across multiple item categories. Additionally, since the firm's bidders are scattered worldwide, large transaction costs are associated with bidding on other soccer-related items, such as a dinner with a player or a ticket to a match.

Management. The managerial team remained constant during the period under study. The founders also have previous successful entrepreneurial experiences in internet companies.

In conclusion, the analysis finds that the average donation does not reflect the optimal one, even after considering several factors that the model omits. The next section empirically supports the thesis that the firm is not maximizing profits and assesses its social impact.

5.1 Prosocial Objectives

In April 2017, a venture capital (VC) fund purchased shares of Charitystars's equity. This section leverages this entry to empirically test whether the firm also sought social returns in addition to profits before the entry. In particular, under the assumption that the VC fund's objective was to maximize the firm's profitability to gain from reselling its shares, the firm should not have changed its "pricing strategy" if it were also maximizing profits before the entry.[31] In contrast, the observation of a drop in the fractions donated (q) after the entry is

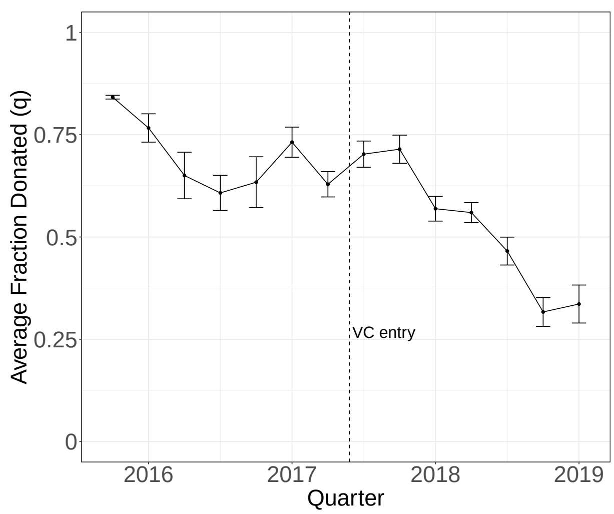
[30] A potential competitor of Charitystars is Charitybuzz. However, Charitybuzz mainly operates in the US and is not present in Europe, which is Charitystars' main market (see Appendix Table C6 for a breakdown of top bidders by nationality). Furthermore, Charitybuzz does not offer charity auctions of soccer jerseys.

[31] Typically, VC funds have a term horizon between three and seven years, after which they will sell for a capital gain. VC funds control the firms in which they invest mainly by advising their management teams (Gompers, 1995), and streamlining certain operational functions such as those related to human resources (Hellmann and Puri, 2002). To maintain a grip on the management teams of the firms they invest in, VC funds

consistent with Charitystars taking social returns into account.

The dataset used to perform this test includes all soccer jersey auctions concluded before November 2018. Figure 6 displays the evolution of the average fraction donated starting from seven quarters before the VC entry to seven quarters after it. The dashed vertical bar in April 2017 signals the time of entry. Across quarters, the average fraction donated was relatively flat in the pre-period, with average donations consistently above 0.65. The average fraction donated dropped considerably from 0.70 before the entry to only 0.52 (one-sided p-value $< 0.1\%$). This drop was not immediate: the fraction donated stayed constant in the first two quarters after the entry and started to decline only from the third quarter onward, with a series of negative jumps. The delay might signal both inventories – this explanation is not fully convincing since Charitystars auctions its items quickly after receiving them – and a time lag needed for the VC fund to influence the firm strategy. Eventually, the average fraction donated reached a value close to 0.25, which is the optimal fraction donated according to the structural analysis.

Figure 6: Average fraction donated per quarter



Note: The average fraction donated per quarter. The vertical line indicates the time of the investment of the venture capital fund. The vertical bars show the corresponding 95% confidence intervals. Only auctions where 85% or less of the price was donated and where the item was sold are considered.

These results support the thesis that Charitystars also considered social objectives. However, the lack of a control group to compare the change in the firm's behavior undermines this interpretation. For instance, the items sold in the post-entry period might differ from

engage in multiple financing rounds where future share-prices are a function of current financial targets (e.g., Cornelli and Yosha, 2003, Tian, 2011). The entering VC fund does not have a stated social mission; it invests in firms with Italian-led management teams, scalable businesses, and international appeal. With a light business structure based mainly on variable costs and an international userbase, Charitystars matches all these criteria.

those sold earlier, or the number of auctions might have increased substantially due to a more efficient procurement process. Accounting for item characteristics and charity and time fixed effects, the average fraction donated after the entry declined, at least, by 0.32. As a result of this change, net revenues increased by 54%, on average, with no detrimental effect on the number of bidders and weekly auctions. Finally, despite the drop in the fraction donated, procurement costs also decreased after the entry, implying savings of €40 per listing. The details of these analyses are in Online Appendix C.1. Therefore, the high fractions donated before the entry should not suggest a challenging procurement process or an incentive for bidders; instead, it signals the firm's double bottom line.

Before analyzing the welfare consequences of social impact, two additional caveats need consideration: the exogeneity of VC financing and the intentions of the founders who sold shares to the VC. Concerning the first point, Charitystars could have set a high fraction donated during the pre-entry period to attract investors. Although this hypothesis is not inconsistent with the firm's broader social objectives, it does not stand up to further scrutiny. First, Charitystars effectively burned cash flows by making hefty donations during the pre-entry period, thereby increasing its need for external financing, which could hinder its growth prospects and survival (e.g., Zingales, 1998, Huynh *et al.*, 2012). Second, burning cash flows accelerate the need for external financing, leading shareholders to sell a company's shares at lower prices. Hence, shareholders effectively traded future money from later venture capital rounds for immediate social impact. Finally, the need for professional advising is not crucial for Charitystars, as its CEO and management team members already had experience as entrepreneurs of successful online companies before founding Charitystars. Concerning the second caveat, understanding why prosocial entrepreneurs would sell shares and agree to turn their businesses around is impossible without information on the shares purchased by the VC, the price paid, and the usage of these funds by the selling shareholders, because whether the shareholders employ the proceeds of the sale for other prosocial activities or for personal consumption matters to assess their preferences. Examining what factors lead shareholders to sell stakes in similar firms is an exciting question for future research.

5.2 Welfare Analysis

Does social impact increase welfare? In Charitystars's economy, welfare is the sum of the firm's profit, the charities' fundraising, and the bidders' surpluses. The first term is defined in Equation 4.1 and the second term is the sum of the procurement costs in the first column of Table 5 and the q portion of the expected price. Lastly, Equation 3.3 defines a bidder's utility.[32] Since the firm is for-profit, the analysis ignores fractions donated greater than one.

The bars of Panel (a) of Figure 7 stack the welfare contribution of each agent for a given donation level. Welfare increases almost linearly from €703 to €1,177 per listing, namely, by 67.5% if a noncharity auction ($q = 0$) is turned into a full charity auction ($q = 1$). This expansion in consumer surplus drives the increase in welfare and is driven by the externality across bidders (α). If α were zero, consumers would perceive donations as price discounts, and the firm could easily capture them, increasing its profits. Since α is positive, consumer surplus increases in the fraction donated, as bidders also derive utility from each others' bids. As discussed in Section 3.4.2, the firm cannot capture this additional surplus from bidders because the pass-through of donations to net revenues is negligible. As a result, the combined surplus to the firm and the charity does not vary substantially with the fraction donated, suggesting that the charity extracts surplus from the firm (light gray bars) rather than from consumers (dark gray bars).

Although total welfare increases, the firm suffers a loss at the social planner's first-best outcome, as Charitystars's profits decrease for fractions donated greater than the profit-maximizing one. If it had no social motives, the firm would optimally deviate from $q = 1$ toward the profit-maximizing q^* of 0.25. At this level, the total surplus is €394 less than its maximum value (a 34% decrease), and the firm's profits are €144 per listing. However, shifting from the first-best outcome to the profit-maximizing q is exceptionally costly for charities and consumers, whose combined surplus per listing would almost halve.

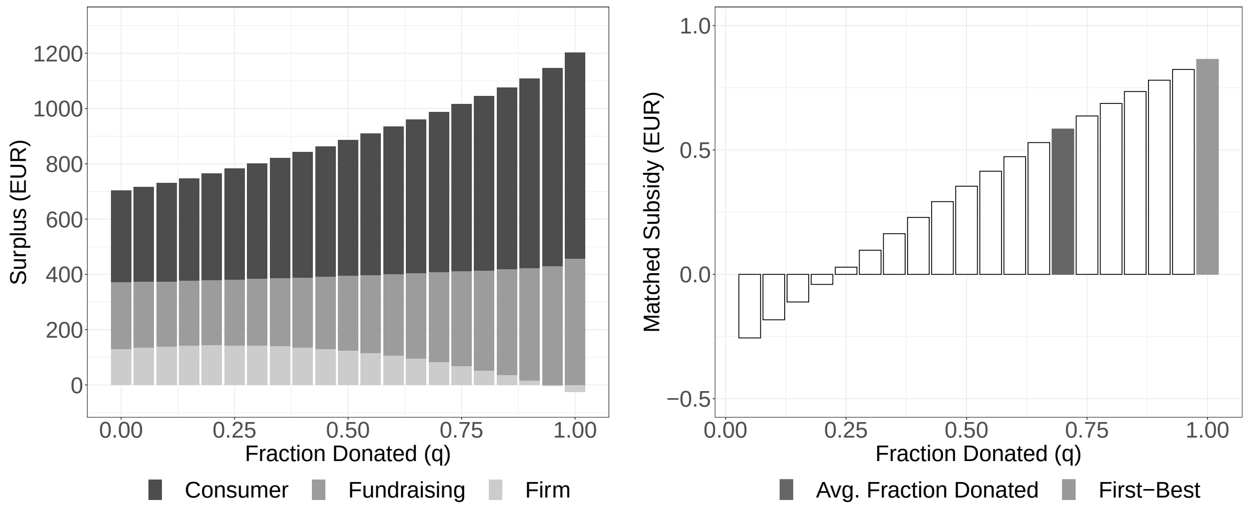
Overall, the firm's social motives cause the combined surplus to consumers and charities to be 42% greater than that of a selfish firm. Without the need for further policy-making, these social motives generate a welfare level that is arguably close to the first-best outcome, recovering 75.3% of the maximum welfare (€906). Inducing a selfish firm to create this level of welfare would require a matched subsidy system awarding the firm €0.58 for each euro that bidders donate – see the dark gray bar in Panel (b) of Figure 7. The first-best outcome costs instead €0.86 per euro donated (light gray bar).[33] These values are not far from income tax deductions available for charitable donations in most developed countries.

[32] To account for auction heterogeneity, values expressed in utils from Equation 3.3 are transformed into the "currency" of the median auction by multiplying them by a conversion factor: the ratio of the expected price of the median auction, namely, $\exp\left(\int_v b(v;\alpha,\beta,q)\, \mathrm{d}F^{(2)}_{(n)}(v) + median(\mathbf{x}\hat{\gamma})\right)$, over the expected price in the absence of covariates, $\int_v b(v;\alpha,\beta,q)\, \mathrm{d}F^{(2)}_{(n)}(v)$, where $\hat{\gamma}$ is the vector of demand estimates from Equation 3.6 and n is the number of bidders. Despite the focus on the median auction heterogeneity, the qualitative results are robust to other levels of auction heterogeneity. Lastly, recall that consumers can derive satisfaction also from the direct payment to the charities. In this case this analysis presents a lower bound for total welfare.

[33] With subsidies, the firm's problem in Equation 4.2 becomes $\max_q (1-q)\cdot p^e - c(q) + s \cdot q \cdot p^e$, where p^e denotes the expected price as a function of q.

Figure 7: Welfare analysis

(a) Surplus by agent and fraction donated (b) Social motives as matched subsidies



Note: Panel a. The total welfare generated by different fractions donated. Total welfare includes (i) consumer surplus – i.e., the expected utility to a bidder according to Equation 3.3 times the number of bidders; (ii) producer surplus – i.e., the expected price net of the donation minus the direct payment paid to purchase the item; and (iii) the fundraising or charity surplus – i.e., the direct payment plus the q-portion of the transaction price. Panel b. The incentive compatible subsidy to the firm at different fractions donated. For each q, the subsidy is computed as a fraction of the expected donation. The dark and light gray bars represent the average observed fraction donated ($\simeq 0.7$) and the welfare-optimizing fraction donated (1.0), respectively. All the values are transformed into euros based on the heterogeneity level of the median auction. The computations assume cubic spline approximations for the density $f(v)$ and the distribution $F(v)$ and that the number of potential bidders is the average observed number in both panels.

5.2.1 Normative Implications

Abstracting from the specific setting, the welfare analysis stresses two main insights. First, it shows researchers that the returns of prosocial programs are not necessarily monotonic in the measure of prosociality. If that were the case, researchers could merely compare the financial returns to firms with high and low values of an underlying social responsibility index (e.g., Thomson Reuters ESG Scores) to determine whether social responsibility increases profitability – a fundamental question in social responsibility research (e.g., Margolis *et al.*, 2007, Flammer, 2015). However, the analysis in this paper demonstrate that the monotonicity assumption does not necessarily hold and that a firm's "prosocial production function" might well be hump-shaped like more general production functions studied in industrial organizations. This observation illustrates the difference between intensive and extensive margins of social responsibility: focusing only on the extensive margin, namely, comparing firms at the opposite tails of an index, could fail to address the profitability question because (i) firms in both groups might not be profit-maximizers even if all firms have the same prosocial production function (e.g., the profit-maximizing firms could be in the middle of the distribution), and (ii) prosocial investments are endogenous to firms' objectives and characteristics, which might vary across firms. Thus, results from cross-firms comparisons could be elusive, leading to erroneous explanations of prosocial choices.

Regarding policy, the analysis emphasizes the identification of the stakeholders concerned by the prosocial programs. Without this step, it would be impossible to assess the distributional implications of social impact for large corporations.[34] While social responsibility indices are reasonable aggregate measures that consumers might recall easily after being exposed to them, the welfare analysis above relegates consumers to a wingman role, as the central tension is between the payoffs to suppliers – charities in this case – and the firm. Therefore, at least in theory, better social responsibility measures would help policymakers target different actors by carefully choosing optimal subsidies and taxes by leveraging the definition of social impact as a tradeoff. More realistically, this exercise shows that social motives can increase welfare without policy intervention as firms internalize their externalities. Most Western countries have adopted policies to sustain firms jointly pursuing financial and social missions to encourage this behavior. The following section concludes the paper by reviewing these legislative efforts in light of these findings.

5.2.2 Positive Implications

Given the analysis presented in the previous sections, this section draws insights for a recent policy debate over how to best support socially-motivated for-profit firms by placing a particular focus on the benefit corporation (BC) legal status, which is, at the time of writing, the only such policy across most Western countries.

The BC status is a recent legal innovation that legally shelters the dove-tailed mission of benefit corporations from transformational takeovers. In the American Bar Association's Business Law Today, Montgomery (2016) wrote that BC laws are "the most significant development in corporate law since [...] 1811," because they overturn the traditional shareholder supremacy model that is responsible for myopic approaches to business due to its focus on shareholders' short-term financial results (Hiller, 2013). In contrast, other legal scholars are skeptical, as they deem BC laws unnecessary (MacLeod Heminway, 2017, Molk, 2017), and feel that the concept of social impact is vaguely defined (Westaway and Sampselle, 2012) because, for example, it sets no priorities in the order of satisfaction of stakeholders (Callison, 2012).

This paper informs this debate by providing a precise definition of social impact based

[34] For instance, Alfaro-Ureña *et al.* (2021) find that the rollout of responsible sourcing programs by large multinational companies differently affected low- and high-skilled workers in Costa Rica, reducing inequality.

on the intensive margin tradeoff defined in this paper. Furthermore, the results of this paper underscore a meager pass-through of social impact costs on consumers, calling into question the sustainability of social impacts. As the BC status comes with legal fees and bureaucratic burdens due to its reporting duties, Charitystars's case suggests that there might be selection into this status, implying that BC firms would not behave differently if they were incorporated as standard for-profits instead. These concerns extend beyond Charitystars due to the growing number of for-profit firms with social missions. For instance, according to Koehn (2016), there were only 1,100 BC firms in the U.S. as of December 2014, while Berrey (2018) counted no less than 7,704 BC firms three years later.[35] Future iterations of BC laws could draw on a similar definition of social impact to better characterize benefit corporations and prioritize stakeholders.

Legal status changes do not directly affect the profitability of for-profit social impact firms. Similar nonprofit firms are greatly fiscally favored via either tax exemptions or lower tax rates, even though their impact on welfare is often dubious. The health care provision market can be taken as an example of a market dominated by nonprofit firms that compete with for-profit firms (Gaynor *et al.*, 2007). A substantial body of academic research finds that nonprofit hospitals behave according to the standard theory of the firm. For instance, Vita and Sacher (2001) show that mergers across nonprofit hospitals increase prices but not quality, Mukamel *et al.* (2002) find that Californian nonprofit hospitals cut clinical expenditures when facing greater competition, which increases mortality rates; moreover, Moon and Shugan (2020) show that nonprofit hospitals are more profitable than for-profit hospitals due to their different product mixes and higher prices. However, tax benefits to nonprofit hospitals alone costed taxpayers $24.6 bn in 2011 (Rosenbaum *et al.*, 2015).

In this context, the findings in this paper call for a new approach to subsidy distribution. A potential solution for this disparity of treatment would be to extend certain benefit corporation transparency requirements to nonprofits. In particular, subsidies could be linked to the results of the yearly third-party audit of social impact that is currently required of BC firms, rather than a firm's legal status. However, a body of theoretical (e.g., Holmstrom and Milgrom, 1991) and empirical evidence (e.g., Fioretti and Wang, 2022) demonstrates that pecuniary incentives can distort effort and that firms can game pay-for-performance

[35]The number of firms with social missions is undoubtedly much larger than the number of BC incorporated firms, which is also likely underestimated. Berrey (2018) mentions several obstacles to obtaining BC data, as databases are decentralized across U.S. states, and their records are often incomplete (e.g., many states do not record the social mission statements in the incorporation articles). According to Dorff *et al.* (2021), BC firms that received early-stage funding include the fin-tech insurance firm Lemonade ($480 m, publicly listed as of 2021), the shoemaking firm Allbirds ($70 m), the internet portal Change.org ($72 m), and the health technology firm Lung Biotechnology ($50 m). Incorporation should not be confused with certification. B Lab-certified firms include both established (e.g., several Danone's subsidiaries and Ben & Jerry's) and young firms (e.g., Kickstarter).

indices due to their informational advantage over regulators.[36] A comprehensive analysis of the practical implementation issues of this proposal is outside of the scope of this paper. Future research might consider these aspects to strengthen the efficiency of public spending by linking subsidies to firms with their provision of social goods.

6 Conclusions

This paper studies social impact as an externality flowing from for-profit firms with social missions to agents outside the firm. The main advantage of this approach is opening up the black box of social impact to understand the welfare implications for concerned agents. This framework is applied to study the operations of Charitystars, a for-profit firm whose social mission influences both consumers and suppliers, but it extends to other firms more generally given suitable data. The paper performs counterfactual demand and supply analyses and finds a mild pass-through of prosocial expenses to consumer demand. Given the salience of the firm's prosocial expenses to consumers, this result highlights that consumers might have a limited role in explaining corporate prosocial expenses. Therefore, social impact implies a tradeoff between the payoffs to the firm and its suppliers rather than between the payoffs to the firm and its consumers, suggesting new avenues of research as most of the social responsibility literature focuses on consumer choices. The paper finds that the firm's social mission allows the recovery of almost 80% of the welfare that a social planner would generate, pointing to a fundamental role for public policies supporting the sustainability of firms with a double bottom line.

[36] Pursuing similar policies requires careful consideration of how subsidies affect corporate governance (e.g., Glaeser, 2002, Guiso *et al.*, 2015) and the motivations and incentives of employees and managers (e.g., Fehr and List, 2004, Besley and Ghatak, 2005, Kolstad, 2013) across nonprofits and benefit corporations.

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Caring or Pretending to Care?
Social Impact, Firms' Objectives and Welfare

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Online Appendix

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Online Appendix

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A Theoretical Appendix

A.1 Lemma A1

The results in this lemma are used in the proof of 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, $b(\overline{v}) = \frac{\overline{v}}{1+q\alpha-q\beta}$ implies that $b(\overline{v}) < \overline{v}$.[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 $b(v) < v \; \forall v \in (\hat{v}, \overline{v}]$.

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

$$(\alpha - \beta) \cdot q = \frac{1}{v} \int_{v}^{\overline{v}} \left(\frac{1 - F(x)}{1 - F(v)} \right)^{\frac{1-q\cdot\beta}{q\cdot\alpha}+1} \mathrm{d}x,$$

which is obtained substituting $b(v) = v$ in the left-hand side of Equation 3.4. Multiplying both sides of the equation by $(1/q\alpha) \cdot f(v)/[1 - F(v)]$ gives

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

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

$$\frac{\partial b^*(v;\alpha,\beta,q)}{\partial v} = \begin{cases} \frac{1}{q\cdot\alpha} \int_{v}^{\overline{v}} \left(\frac{1-F(x)}{1-F(v)} \right)^{\frac{1-q\cdot\beta}{q\cdot\alpha}+1} \mathrm{d}x \cdot \frac{f(v)}{1-F(v)} > 0, & \text{if } \alpha > 0 \wedge q > 0 \\ \frac{1}{1-q\cdot\beta} > 0, & \text{if } \alpha = 0 \vee q = 0. \end{cases} \tag{A.2}$$

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 $v \in (v_3, \overline{v}]$ and $b(v) > v$ for $v \in (\underline{v}, v_1)$ and $v \in (v_2, v_3)$. The increasing hazard rate property gives

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

[1] This result comes from applying L'Hospital's rule to $\int_{V}^{\overline{v}} \left(\frac{1-F(x)}{1-F(V)} \right)^{\frac{1-q\beta}{q\alpha}+1} \mathrm{d}x$ and from exploiting the increasing hazard rate assumption.

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

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

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 A1a provides a graphical representation. Because v_1,v_2 and v_3 are arbitrary values, the proof holds for all v. Given that $b(\underline{v}) \geq \underline{v}$, $b(\overline{v}) < \overline{v}$ 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: $b(\underline{v}) < \underline{v}$. 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 $(\tilde{v},\overline{v}]$, where $\tilde{v} \in [\underline{v},\overline{v}]$, 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)* establishes that for $\beta \geq \alpha > 0$ the bid is increasing in q $\forall v$. *(Step 2)* focuses on the remaining case ($\beta < \alpha$) and shows that the derivative of the bid w.r.t. q can have both positive and negative values. *(Step 2.a)* shows 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. Finally, *(step 2.b)* shows the conditions for the uniqueness of $\tilde{v}$.

Step 1: $\beta \geq \alpha > 0$ *.* The derivative of Equation 3.4 w.r.t. q for $\alpha > 0$ is

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

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. $\frac{\partial b(v)}{\partial q}|_{v=\tilde{v}} = 0$. Rewriting Equation A.3 and evaluating it at $\tilde{v}$ yields

$$\begin{aligned}
-\int_v^{\overline{v}} \left(\frac{1-F(x)}{1-F(v)}\right)^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}} \frac{\alpha(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}^2}\log\frac{1-F(x)}{1-F(v)}\mathrm{d}x &= (\alpha-\beta)\left(v+\int_v^{\overline{v}}\left(\frac{1-F(x)}{1-F(v)}\right)^{\frac{1-\tilde{\beta}}{\tilde{\alpha}}+1}\right)\mathrm{d}x\Bigg|_{v=\tilde{v}} \\
&= (\alpha-\beta)(1+\tilde{\alpha}-\tilde{\beta})b(\tilde{v}).
\end{aligned} \tag{A.4}$$

where the second line replaces the expression to the right-hand side with the optimal bid function in Equation 3.4. 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

$$-\int_{\tilde{v}}^{\overline{v}} \left(\frac{1-F(x)}{1-F(\tilde{v})}\right)^{\frac{1-\tilde{\beta}}{\tilde{\alpha}}+1} \alpha\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}^2}\left(1+\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}\log\frac{1-F(x)}{1-F(\tilde{v})}\right)\mathrm{d}x\frac{f(\tilde{v})}{1-F(\tilde{v})}, \tag{A.5}$$

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

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

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

$$- \left(b(\tilde{v})(1+\tilde{\alpha}-\tilde{\beta}) - \tilde{v}\right) \alpha \frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}^2} + (\alpha-\beta)\frac{(1+\tilde{\alpha}-\tilde{\beta})^2}{\tilde{\alpha}} b(\tilde{v}) \leq \frac{(\alpha-\beta)(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}} \left(b(\tilde{v})(1+\tilde{\alpha}-\tilde{\beta}) - \tilde{v}\right)$$

$$\Rightarrow b(\tilde{v}) \geq \tilde{v}.$$

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 $v \to \overline{v}$ 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

$$\lim_{v \to \overline{v}} \frac{\int_v^{\overline{v}} (1-F(x))^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}} \left(-\frac{\alpha(1+\tilde{\alpha}-\tilde{\beta})}{\tilde{\alpha}^2} \log \frac{1-F(x)}{1-F(v)} - (\alpha-\beta)\right) \mathrm{d}x}{(1+\tilde{\alpha}-\tilde{\beta})^2 (1-F(v))^{\frac{1+\tilde{\alpha}-\tilde{\beta}}{\tilde{\alpha}}}} = 0,$$

while the limit of the remaining part is $\lim_{v \to \overline{v}} -(\alpha-\beta)v = -(\alpha-\beta)\overline{v} < 0$. 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 one need 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, $\tilde{\tilde{v}}$ such that $b(v) > v$ for $v < \tilde{\tilde{v}}$ and $b(v) < v$ for $v > \tilde{\tilde{v}}$. 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, $\tilde{v} < \tilde{\tilde{v}}$ as otherwise $\partial b(v)/\partial q|_{v=\overline{v}} > 0$. In fact, Equation A.3 is increasing at $\tilde{v}$ for $\tilde{v} \geq \tilde{\tilde{v}}$, 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 $\partial b(v)/\partial q|_{v=\overline{v}} < 0$ condition, but this is not possible in this region because of $\tilde{\tilde{v}}$ is unique and $b(v) < v$ for $v > \tilde{v} \geq \tilde{\tilde{v}}$. (see Figure A1b).

In addition, the uniqueness of $\tilde{\tilde{v}}$ implies that $\tilde{v}$ does not exists 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 $\tilde{v}$

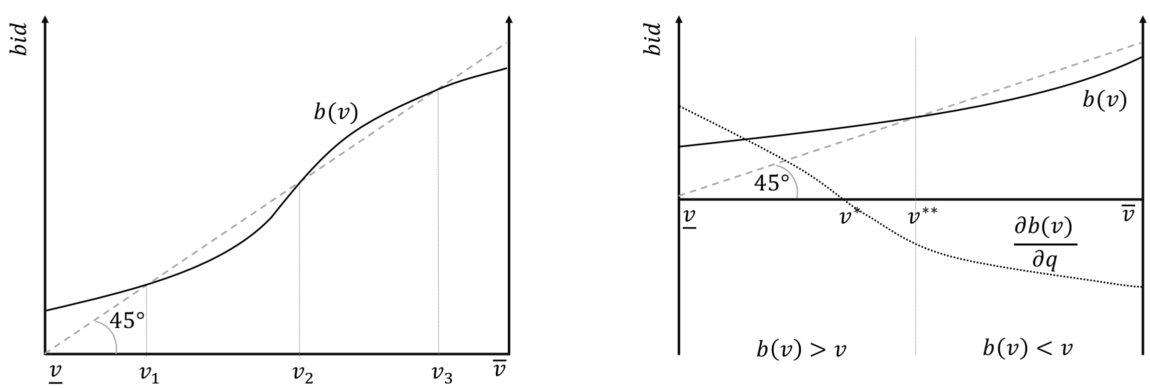
exists, it is unique and separates those who increase their bid (low value bidders) from those who decrease it (high-value bidders).

Step 2.b: Case 2. The second case assumes $b(\underline{v}) < \underline{v}$. Lemma A1 proves that there are either no $\tilde{\tilde{v}}$ or that there are exactly two $\tilde{\tilde{v}}$ 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 A1 and Lemma 1

(a) Lemma A1 (b) Lemma 1



Note: Panel a. The panel 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. Panel b. The panel shows the effect of a marginal increase in q when $\alpha > \beta$ assuming that $b(\underline{v}) > \overline{v}$. 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.

A.3 Proof of Proposition 1

The net revenue-optimal fraction donated q^R

- *solves* $\eta(p^e(q_R), q_R) = \frac{q_R}{1-q_R}$ *for* $\alpha > 0$*, where* $\eta(p^e, q) = \frac{\partial p^e}{\partial q}\frac{q}{p^e}$ *is the elasticity of the expected price,* p^e*, to the fraction donated,* q*;*
- *is equal to 0 when* $\alpha = 0$.

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

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

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

$$\int_{\underline{v}}^{\overline{v}}(1-q)\cdot b(v,q)\mathrm{d}F_{(n)}^{(2)}(v).$$

Denote the expected price by $p^e=\int_{\underline{v}}^{\overline{v}}b(v,q)\mathrm{d}F_{(n)}^{(2)}(v)$ 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 $\frac{\partial p^e}{\partial q}=\int_{\underline{v}}^{\overline{v}}\frac{\partial b(v,q)}{\partial q}\mathrm{d}F_{(n)}^{(2)}(v)$. Using the elasticity formula, $\int_{\underline{v}}^{\overline{v}}\frac{\partial b(v,q)}{\partial q}\mathrm{d}F_{(n)}^{(2)}(v)=\eta\frac{p^e}{q}$.

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

$$\int_{\underline{v}}^{\overline{v}}-b(v,q)+(1-q)\cdot\frac{\partial b(v,q)}{\partial q}\mathrm{d}F_{(n)}^{(2)}(v)=0.$$

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: Let us first derive the first-order condition of the bidder problem as in Equation 3.5. Denote by $F_{(n)}^{(k)}(v)$ the distribution of the $k-$th highest element out of n. The proof then assumes that a monotonic and differentiable bidding function $b(v;\alpha,\beta,q)$ exists and it studies the decision of a bidder who maximizes her utility, $\mathcal{U}(v,s;\alpha,\beta,q)$, by choosing to bid as if her private value were s instead of v. The bidder's problem in Equation 3.3 can be rewritten as

$$
\begin{aligned}
\mathcal{U}(v,s;\alpha,\beta,q) = & \int_{\underline{v}}^{s} \left[v - (1-\beta\cdot q)\cdot b(u;\alpha,\beta,q)\right] dF(u)^{n-1} \\
& + \alpha\cdot q\cdot b(s;\alpha,\beta,q)\cdot(n-1)\cdot F(s)^{n-2}\cdot[1-F(s)] + \alpha\cdot q\cdot\int_{s}^{\overline{v}} b(u;\alpha,\beta,q)dF^{(2)}_{(n-1)}(u),
\end{aligned}
$$

which terms are defined in Section 3.2.1. The symmetric Bayes Nash equilibrium is found at

$$
\begin{aligned}
\left.\frac{d\mathcal{U}(v,s;\alpha,\beta,q)}{ds}\right|_{s=v} =& 0 \\
=& v\cdot\frac{\partial F(s)^{n-1}}{\partial s} + (\beta\cdot q-1)\cdot b\cdot\frac{\partial F(s)^{n-1}}{\partial s} + \alpha\cdot q\cdot b\cdot(n-2)\cdot\frac{\partial F(s)^{n-1}}{\partial s}\frac{1-F(s)}{F(s)} \\
& + \alpha\cdot q\cdot b'\cdot(n-1)\cdot[1-F(s)]\cdot F(s)^{n-2} - \alpha\cdot q\cdot b\cdot\frac{\partial F(s)^{n-1}}{\partial s} \\
& - \alpha\cdot q\cdot b\cdot(n-2)\cdot\frac{\partial F(s)^{n-1}}{\partial s}\frac{1-F(s)}{F(s)} = 0,
\end{aligned}
$$

where b and b' denote a bid function and its derivative, respectively. Deleting and moving term yields

$$
v\cdot f(v) = (1+q\cdot\alpha - q\cdot\beta)\cdot b(v)\cdot f(v) - q\cdot\alpha\cdot b'(v)\cdot[1-F(v)]. \qquad \text{(A.7)}
$$

I use this Equation for identification of $\{F(v),\alpha,\beta\}$.[2] Part 1 focused on the case where all bids are observed. The second part of the proof considers the case when only the winning bids (and the number of bidders) are observed.

Part 1. All Bids Are Truthful. Under Assumption A.7 the distribution of private values is equal to the observed distribution of bids, $F(v) = G(b(v;\alpha,\beta,q);q)$. Therefore, Equation A.7 can be rewritten as

$$
v = (1+\alpha\cdot q - \beta\cdot q)\cdot b - \alpha\cdot q\cdot\lambda_G(b;q), \qquad \text{(A.8)}
$$

where the inverse hazard rate of the distribution of bids evaluated at a bid equal to b is denoted by $\lambda_G(b)$. In this equation, the only unknowns are v, α and β as in Equation 3.5. The bids b and its inverse hazard rate are observed.

The researcher observes two types of auction, A and B, such that the only difference between the two auction types is the fraction donated (i.e., $q^A \neq q^B$). Because bids are monotonic in v, at each private value, v_τ, corresponding to the τ-quantile of the private

[2] This differential equation can be finally solved by multiplying both sides of (A.7) by $-\frac{[1-F(s)]^{\frac{1-q\beta}{q\alpha}}}{q\alpha}$ and integrating, which yields the bid function in Equation 3.4.

value distribution, the observed distributions of bids for auctions A and B are such that $G(b_\tau; q^A) = G(b_\tau; q^B)$. Matching Equations A.8 upon the quantiles of the two bid distributions for auctions of type A and B yields the following condition

$$v_\tau^A - v_\tau^B = b_\tau^A - b_\tau^B + (\alpha - \beta) \cdot (q^A \cdot b_\tau^A - q^B \cdot b_\tau^B) - \alpha \cdot \left(q^A \cdot \lambda_{G^A}(b_\tau^A) - q^B \cdot \lambda_{G^B}(b_\tau^B) \right), \tag{A.9}$$

for each τ quantile, where b_τ^x denotes the observed bid in auction $x \in \{A, B\}$ at the τ quantile of its bid distribution, and $\lambda_G(b_\tau^x)$ $(= \lambda_G(b_\tau; x))$ denotes the inverse hazard rate computed on b^x and evaluated at the τ quantile of auction x's bid distribution. Assumption 2 implies that $v_\tau^A - v_\tau^B = 0$, and thus the true parameters $\{\alpha_0, \beta_0\}$ are the solution of the system of Equations A.9. To show that a solution exists and is unique, rewrite Equation A.9 in matrix notation as

$$\Delta(b) = \mathbf{B} \times \begin{bmatrix} \alpha - \beta \\ -\alpha \end{bmatrix},$$

where $\Delta(b) = -(b^A - b^B)$ stacks all $[b_\tau^A - b_\tau^B]$ differences and $\mathbf{B}$ is the matrix stacking $[q^A \cdot b_\tau^A - q^B \cdot b_\tau^B; \quad q^A \cdot \lambda_G(b_\tau^A) - q^B \cdot \lambda_G(b_\tau^B)]$. The matrix $\mathbf{B}$ has full rank. To prove this assume to the converse that $\mathbf{B}$ is not invertible, meaning that its columns are linearly dependent. Therefore, $b_\tau^x = k \cdot \lambda_G(b_\tau^x)$ for $x \in \{A, B\}$. It follows that,

$$G(b_\tau^x) = 1 - b_\tau^x \cdot g(b_\tau^x)/k, \tag{A.10}$$

for a constant $k > 0$. Note that k must be positive because otherwise $G(b_\tau^x) > 1$ as $g(b_\tau^x) \geq 0$, $\forall\, b_\tau^x$. The differential Equation A.10 admits a solution $g(b_\tau^x) = c \cdot (b_\tau^x)^{-(k+1)}$, where c is an integration constant. Thus, $G(b_\tau^x) = 1 - c \cdot (b_\tau^x)^{-k}/k$. Evaluating the CDF at $b_\tau^x = 0$ yields $G(0) = -\infty$, $\forall\, k > 0$. Moreover, the inverse hazard rate,

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

is increasing in b_τ^x. This implies that

$$\frac{1 - F(v_\tau)}{f(v_\tau)} = \frac{1 - G(b(v_\tau; \alpha, \beta, q)}{g(b(v_\tau; \alpha, \beta, q) \cdot b'(v_\tau; \alpha, \beta, q)} = \frac{1}{k} \frac{b(v_\tau; \alpha, \beta, q)}{b'(v_\tau; \alpha, \beta, q)},$$

which is an increasing function because the optimal bidding function, $b(v; \alpha, \beta, q)$, (i) is increasing in v and (ii) maximizes a bidder's utility (i.e., $b''(v; \alpha, \beta, q) \leq 0$). This means that the inverse hazard rate is not decreasing and that therefore $b(v_\tau; \alpha, \beta, q)$ is not a best response for v_τ. A contradiction. Therefore, the columns in $\mathbf{B}$ are not linearly dependent and that $\mathbf{B}$ is invertible. Therefore, the system of Equation A.9 admits a unique solution for $\{\alpha, \beta\}$.[3] Given that $\mathbf{B}$ has full rank, $\{\alpha, \beta\}$ are nonparametrically identified. $F(v)$ is then nonparametrically identified by plugging $\{\alpha, \beta\}$ in Equation A.8.

Part 2. Online Auctions. The second part of the proof extends the previous result to online auctions. The proof still maintains that two auction types $\{A, B\}$ are observed such that $q^A \neq q^B$.

First, the two distributions of the winning bid, $G_w(b^x)$ for $x \in \{A, B\}$, are identified from data on winning bids for the two sets of auctions. In equilibrium, the distribution of the winning bid is equal to the distribution of the second-highest bid, $G_w(b^x) = G^2_{(n)}(b^x)$, for $x \in \{A, B\}$. Therefore, $G(b^x)$ is found as the root (in $[0,1]$) of $G_w(b^x) - nG(b^x)^{n-1} + (n-1)G(b^x)^n = 0$. Second, these two distributions (instead of the empirical distributions of bids) are needed to rewrite Equation A.7 as Equation A.8. Third, the same logic shown in Part 1 is applied to identify α, β from A.9, and $F(v)$ from A.8, using only 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, let b^x_τ be the bid in an auction where x is the fraction donated that refers to the τ-quantile of its bid distribution. The inverse hazard computed at b^x_τ is $\lambda_G(b^x_\tau) = \frac{1-G(b_\tau;q^x)}{g(b_\tau;q^x)}$. The dimension of q is $K_Q > 2$ (see Proposition 2 for $K_Q = 2$), and K_τ quantiles of the distribution of bids are observed for each auction type. The FOC Equation 3.5 in matrix notation becomes

$$\underset{K_\tau \cdot K_Q}{V} = (\alpha - \beta) \cdot \underset{K_\tau \cdot K_Q}{B} \cdot \underset{K_Q \cdot K_Q}{Q} + \underset{K_\tau \cdot K_Q}{B} - \alpha \cdot \underset{K_\tau \cdot K_Q}{\Lambda} \cdot \underset{K_Q \cdot K_Q}{Q}, \qquad \text{(A.11)}$$

where V is a matrix of dimension $K_\tau \times K_Q$ displaying the value v_τ for the $\tau-$quantile (row) in auctions where q is the fraction donated (column), and 0 otherwise. Similarly, Q is a diagonal matrix with entries equal to the fraction donated q and 0. The other matrices are

[3] If $k = 1$, then $g(b^x_\tau) = 0$ for $b^x_\tau < 0$ and $g(b^x_\tau) > 0$ for $b^x_\tau \geq 0$. 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, which contradicts Assumption 1.

defined as:

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

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

There exists a projection M (with rank $K_Q - 1$) such that $V \times M = 0$. Post-multiplying Equation A.11 by M and moving terms, the following equation represents the FOC where the dependent variable is a known object

$$-B \cdot M = (\alpha - \beta) \cdot B \cdot Q \cdot M - \alpha \cdot \Lambda \cdot Q \cdot M.$$

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

$$y = \begin{bmatrix} b & l \end{bmatrix} \cdot \begin{bmatrix} \alpha - \beta \\ -\alpha \end{bmatrix},$$

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

The 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 4.2 in Section 4. 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

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

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

$$-p^e\left(\frac{(1-\omega)\cdot((1-q)\cdot p^e-\kappa)}{\omega\kappa+q\cdot((1-q)\cdot p^e-\kappa)}\right)=\frac{1-q}{q}\cdot\eta\cdot p^e-p^e, \tag{A.12}$$

where η is the elasticity of the expected price to a change in q. The right-hand side is the same as in Equation 4.2, 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 4 ($c'(q)$). 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 monopolist model presented in Section 4.

Finally, the left-hand side in Equation A.12 can be rearranged by adding and subtracting $1/q$ in the term in parentheses

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

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

B Data Description

The dataset is collected from the company website pages dedicated to soccer items (`www.charitystars.com`). The main dataset employed for the demand and supply analyses ranges from July 1, 2015, to June 12, 2017. This dataset includes only actually worn soccer jerseys and official jerseys signed by athletes. Auctions for training jerseys, jerseys from third-division teams (e.g., Italian Lega Pro), jerseys without footballer numbers on the back, jerseys from friendly matches among retired footballers, jerseys from Chinese or US soccer teams, and auctions of jerseys with special patches or ads are excluded from this dataset to improve the comparability of the data across auctions; these exclusions reduce the dataset from 1,837 auctions to 1,580 auctions.

All available information for each listing and the corresponding charity and bid history are collected in part manually and in part through a scraping algorithm. This dataset is augmented with data from other sources. First, a similar software is used to recover the relevant footballers' quality scores from a renowned videogame (*Fifa*). Second, information on each charity's mission is collected from both Charitystars and each charity's website. Third, the following information for worn jerseys is recorded manually after being collected from internet sources (mainly newspaper and charity websites): (i) whether the corresponding team won the match and how many goals (if any) the player wearing the jersey scored; (ii) the competition in which the jersey was worn and whether the relevant match was a final of the competition, (iii) the nationality of the team, (iv) whether the team is important, (v) whether the player is on the FIFA 100 list of the best players in soccer history, (vi) the charity mission. Appendix Section B.1 describes all the data in detail.

Certain analyses in Section 5 employ a different dataset that extends to November 8, 2018 and is obtained similarly to the previous dataset. In addition to the chosen charity, time, number of bidders, number of bids placed, reserve price, minimum raise and fraction donated for each auction, the following variables are included to control for whether an auction listing states that the corresponding match or jersey was worn during the Champions League, the Europa League, the Italian Serie A, the English Premier League, the Spanish Liga, the German Bundesliga, the World Cup, or a final and whether the item is a worn jersey, a signed jersey, or an unwashed jersey. Furthermore, the dataset includes variables that denote the length (in days) of each auction (computed from the date on which the first bid was placed), the number of pictures displayed on the webpage, the length of the item description (in words), the length of the charity description (in words), and whether the auction time was extended due to a bid during the last 4 minutes. This new dataset consists of 4,271 auctions that ended with a sale from July 1, 2015, to November 8th, 2018, and 4,117 of them have a fraction donated (q) smaller than or equal to 0.85.

B.1 Description of the Variables

The regression tables in Sections 2, 3.2 and 4 and in the appendices directly mention only selected variables due to space limitations. The analysis considers only a subset of the available auctions as follows: auctions (i) with transaction prices higher than their reserve prices (from 1,580 to 1,538 observations), (ii) with prices between €100 and €1,000 (1,301 observations),[4] (iii) with two or more bidders (1,278 observations), (iv) with minimum increments less than or equal to e 30 (1,270 observations),[5] (v) featuring jerseys that do not belong to a second-division team (1,265 observations), (vi) with donation percentages less than 85% of the final price (1,185 observations), and (vii) that ended with an immediate sale (1,107 observations).[6] The variables are separated into four groups based on their contents and are reported across the regression tables using their group names.[7]

1. **Main variables**: These are the variables used in all the regression tables and in the structural model. They are listed in Table B1, while Table B2 reports the correlations between their cross-correlation coefficients (only for the continuous variables). The meanings of most of the variables are immediately made clear by their labels. The following list describes some of the variables whose labels are less informative.

   (a) The variable *Length* counts the number of days between the first bid and the closing date of an auction (auction starting dates are not available).

   (b) The dummy *Extended time* is equal to 1 if two or more bidders placed a bid during the last four minutes of the focal auction. In such cases, the time is extended by an additional four minutes until all but 1 bidder drops out.

   (c) *Number of same team auctions in past 3 weeks* counts the number of auctions listing jerseys from the same team as that of the focal item. It considers all 1,580 auctions.

[4]These values are the 7.5$^{\text{th}}$ and 92.5$^{\text{th}}$ percentiles of the transaction price distribution. The results still holds with different trimming.

[5]This value is approximately 10% of the median price (€311) of the whole sample. In the main sample, the 90$^{\text{th}}$ (98$^{\text{th}}$) percentile of the minimum raise distribution is €1.12 (€11.35), or approximately 0.31% (3.1%) of the average price. Applying a stricter trimming does not affect these estimates.

[6]If the standing price is lower than the secret reserve price at the end of an auction, Charitystars reveals the reserve price to the highest bidder, who can then decide to pay this price and win the auction. These cases are identified as those with a final bid that was posted after the auction end date and a transaction price equal to the reserve price. In addition, one auction has a reserve price equal to zero, and it is excluded from the structural model estimation. Instruments to account for endogeneity are constructed using observations from concurrent listings (within a 5-day interval) based on the variables presented below but computed over the full sample of 1,580 auctions. Appendix Figure D5 reports the distributions of the number of concurrent auctions (Panel a) and the average value of q (Panel b).

[7]When taking the log of a variable, 1 is added to variables that can take values equal to 0. All results are robust to different similar monotonic transformations and also to excluding the specific observations.

(d) *Number of same player auctions until 2 weeks before the auction* counts the number of auctions for jerseys worn by the same player playing for the same team during the same year as the match of the jersey that is being auctioned. It considers all the listings up to 2 weeks before the end of the auction (Charitystars's auctions last between 1 and 2 weeks). It considers all 1,580 auctions. This variable proxies for the popularity of each item.

(e) *Counter of auctions from same charity* is a progressive count of the number of listings for each charity on the day when the focal auction ends.

(f) The dummy *Player belongs to FIFA 100 list* is 1 if the focal player is on the FIFA 100 list (a list of the best soccer players ever).

(g) The variable *Number of goals scored* is equal to the number of goals scored by the player who wore the auctioned jersey in a particular match if this number is mentioned in the listing. It is zero otherwise.

(h) The dummy *Jersey belongs to an important team* is is equal to 1 if the focal player plays for one of the following teams (alphabetical 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, the Netherlands, PSG, Real Madrid, Sevilla FC, Spain, SS Lazio, SSC Napoli, or Uruguay.

(i) The variable *Fifa 16 overall player quality*refers to the focal player's quality based on the videogame Fifa 16 (using player quality scores from earlier versions of the Fifa video game does not change the results because these scores are highly serially correlated).

(j) *Charity Dummies*: This group includes dummies related to heterogeneity across various charities based on their missions. These dummies are not exclusive bins, as most charities engage in more than one activity. There are 93 different charities in total. The dummy variables used are as follows:

  i. *Charity deals with disabilities* indicates charities involved in assisting disabled people.

  ii. *Charity builds infrastructures in developing countries* indicates charities that build infrastructure in developing countries.

  iii. *Charity deals in healthcare* indicates charities dealing with health care and health research.

iv. *Charity has humanitarian scopes in developing countries* indicates charities that help people in situations of poverty and undernourishment.

v. *Charity deals with children's wellbeing* indicates charities that provide activities (e.g., education and sports) for youth.

vi. *Charity deals with neurodegenerative disorders* indicates charities that help those suffering from neurodegenerative disorders.

vii. *Charity linked to a soocer team* indicates charities that are connected to a football team (e.g., through sponsorship).

viii. *Charity aims to improve access to sport* indicates charities that give individuals integration opportunities through sports activities.

ix. *Charity is English* indicates English charities (most of the examined charities are Italian).

2. **Add. charity dummies**: This is a group of additional charity dummies, which are as follows:

   (a) *Charity deals with emergencies* indicates charities that deal with emergencies (such as by providing funds for the Red Cross in case of large floods).

   (b) *Charity deals with health research* indicates charities that are involved in innovative research (e.g., "Breast Cancer Now").

   (c) *Charity offers surgeries* indicates charities that offer surgeries either directly or by providing transportation services for people who need critical medical attention abroad (e.g., the "Flying Angels Foundation")).

   (d) *Charity deals with cancer, leukemia and diabetes* denotes charities that either do research on these topics or provide support to the family members and children of those affected by these diseases.

   (e) *Children deals with social integration* (e.g., "A Star Foundation").

3. **League/match dummies**: these are dummies related to soccer league and match heterogeneity. They include the following:

   (a) Dummies for jerseys worn in 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*).[8]

[8] All remaining competitions are treated as friendly matches.

(b) Dummies that indicate whether each listing mentions whether the relevant match was won and whether the team is an English team, an Italian Team, a Scottish Team, a Spanish team, or a national team.[9]

4. **Time dummies**: This group includes *day-of-the week* dummies (6 variables), *month* dummies (11 variables) and *year* dummies (1 variable).

Finally, the auction webpages also have information on the nationality of each bidder (if provided by the bidder). Nationalities and usernames were recorded for all but 122 out of the 1,107 auctions in the dataset, and these data were impossible to retrieve, as they were missing at the time of scraping. Appendix Table C6 reports a summary of the nationalities of the top bidders.

[9] These nationalities were chosen because most bidders are from Italy and the UK and a considerable number of objects are sourced from Spanish teams.

Table B1: Summary statistics of main variables

Variable	Mean	St.Dev.	Q(25%)	Q(50%)	Q(75%)
Auction characteristics:					
Fraction donated (q)	0.70	0.27	0.78	0.85	0.85
Transaction price (€)	364.56	187.38	222.80	315.00	453.00
Reserve price (€)	179.01	132.14	100.00	150.00	210.00
Minimum increment (€)	1.69	3.13	1.00	1.00	1.00
Number of bidders	7.84	3.27	5.00	7.00	10.00
Number of bids placed	24.79	18.29	11.00	20.00	34.00
Sold at reserve price (0/1)	0.04	0.20	0.00	0.00	0.00
Web-listing details:					
Length (in # days)	8.09	3.08	7.00	7.00	7.00
Extended time (0/1)	0.43	0.50	0.00	0.00	1.00
Length of description (in # words)	141.82	42.16	123.00	140.00	161.50
Content in English (0/1)	0.30	0.47	0.00	0.00	1.00
Content in Spanish[a] (0/1)	0.00	0.07	0.00	0.00	0.00
Length of charity description (in # words)	123.40	56.54	107.00	107.00	120.00
Number of pictures	5.66	1.99	5.00	6.00	7.00
Player, jersey and match characteristics:					
Number of same team auctions in past 3 weeks	1.47	4.09	0.00	0.00	1.00
Number of same player auctions until 2 weeks before the auction	5.07	7.92	0.00	1.00	7.00
Player belongs to FIFA 100 list (0/1)	0.11	0.31	0.00	0.00	0.00
Fifa 16 overall player quality	71.38	27.99	77.00	81.00	85.00
Unwashed jersey (0/1)	0.09	0.29	0.00	0.00	0.00
Jersey is signed (0/1)	0.52	0.50	0.00	1.00	1.00
Jersey is signed by the team players/coach (0/1)	0.06	0.24	0.00	0.00	0.00
Jersey worn during a final (0/1)	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 (0/1)	0.88	0.32	1.00	1.00	1.00
Charity characteristics:					
Charity is Italian[a] (0/1)	0.90	0.29	1.00	1.00	1.00
Charity is English (0/1)	0.08	0.28	0.00	0.00	0.00
Charity deals with disabilities (0/1)	0.35	0.48	0.00	0.00	1.00
Charity builds infrastructure in dev. countries (0/1)	0.09	0.29	0.00	0.00	0.00
Charity deals in healthcare (0/1)	0.23	0.42	0.00	0.00	0.00
Charity has humanitarian scopes in dev. countries (0/1)	0.14	0.34	0.00	0.00	0.00
Charity deals with children's wellbeing (0/1)	0.84	0.36	1.00	1.00	1.00
Charity deals with neurodegenerative disorders (0/1)	0.06	0.23	0.00	0.00	0.00
Charity linked to the soccer team (0/1)	0.10	0.29	0.00	0.00	0.00
Charity aims to improve access to sport (0/1)	0.63	0.48	0.00	1.00	1.00
Counter of auctions from same charity	128.47	151.96	14.00	54.00	219.00

Note: Overview of the main covariates used in all specifications in the reduced form analysis and in the structural model. The number of observation is 1,107. All the charity descriptions that are not displayed in English or Spanish are in Italian (not shown). Prices are in Euro. If the listing is in GBP the final price is converted in euro using the exchange rate displayed in the source code of the listing HTML page. The maximum number of goals scored with a sold jersey is 2. A superscript [a] indicates that the variable not used in regressions. The number of bids placed is not used in the demand analyses.

Table B2: Correlation matrix for continuous variables

	Reserve price	Number of bidders	Length	Minimum raise	Content description (# of words)	Charity description (# of words)	Number of pictures	Same team auctions in past 3 weeks	Same player auctions until prior 2 weeks	Charity counter	Fifa player quality	Number of goals scored	Fraction donated (q)
Reserve price	1.000												
Number of bidders	–0.065	1.000											
Length	–0.012	0.023	1.000										
Minimum raise	–0.006	–0.088	0.435	1.000									
Content description	0.169	0.061	0.038	0.064	1.000								
Charity description	–0.037	0.006	0.217	0.266	0.168	1.000							
Number of pictures	0.028	0.154	–0.113	–0.117	0.059	0.023	1.000						
Same team auctions in past 3 weeks	0.140	0.021	0.198	0.324	0.210	0.159	0.066	1.000					
Same player auctions until prior 2 weeks	–0.138	0.176	–0.137	–0.118	–0.236	–0.113	0.120	–0.160	1.000				
Charity counter	–0.080	–0.002	–0.233	–0.159	–0.291	–0.243	0.174	–0.157	0.431	1.000			
Fifa player quality	–0.183	0.088	–0.042	0.029	–0.123	–0.081	0.147	0.055	0.264	0.221	1.000		
Number of goals scored	0.074	0.012	0.019	–0.015	0.096	–0.018	–0.099	0.067	–0.040	–0.050	–0.009	1.000	
Fraction donated (q)	–0.265	0.168	0.057	0.039	–0.106	0.029	0.115	0.141	0.026	0.007	0.321	–0.006	1.000

C Omitted Tables

Table C1: Logarithm of transaction prices and fractions donated

Transaction price (ln)	(I) OLS	(II) Q(0.25)	(III) Q(0.50)	(IV) Q(0.75)
Fraction donated (q)	0.188***	0.207***	0.226***	0.257***
	(0.052)	(0.066)	(0.075)	(0.093)
F-test of equality with OLS (p-value)		0.767	0.607	0.456
Main variables	✓	✓	✓	✓
N	1,107	1,107	1,107	1,107

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

Note: OLS and quantile regressions of the logarithm of the transaction price on covariates (continuous covariates except for q are in logs). The null hypothesis that the coefficient of the fraction donated (q) is equal across column (II), (III) and (IV) is not rejected at 0.865 levels (F-test = 0.16). 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 D4. Control variables are defined in Appendix B. Standard errors are obtained by boostrap with 400 repetitions.

Table C2: Fractions donated and past prices and number of bidders

Fraction donated (q)	(I)	(II)	(III)	(IV)	(V)	(VI)
Avg. price (ln)	0.031	0.050	0.067			
	(0.023)	(0.033)	(0.042)			
Avg. number of bidders				0.003	0.016*	0.013
				(0.007)	(0.010)	(0.012)
Main variables	✓	✓	✓	✓	✓	✓
League/match dummies	✓	✓	✓	✓	✓	✓
Time dummies	✓	✓	✓	✓	✓	✓
Charity fixed effects	✓	✓	✓	✓	✓	✓
Average taken across auctions ending within x days earlier	10	20	30	10	20	30
Adjusted R-squared	0.500	0.503	0.504	0.499	0.503	0.504
N	1,094	1,077	1,067	1,094	1,077	1,067

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

Note: OLS regressions of the fraction donated on covariates including either the average price (Columns 1, 2, and 3) or the average number of bidders (Columns 4, 5, and 6) across auctions ending ten, twenty and thirty days earlier. Past auctions include all auctions for soccer jerseys available in the dataset (1,580 auctions), not just the subset described in Section 2. Potentially endogenous covariates such as the reserve price, the number of bidders and an indicator for whether the transaction price is equal to the reserve price are excluded. Control variables are defined in Appendix B. Robust standard errors in parenthesis.

Table C3: OLS and IV regressions of transaction prices on fractions donated.

Transaction price	(I) OLS	(II) IV	(III) IV	(IV) IV
Fraction donated (q)	88.082***	169.925*	168.814*	181.104*
	(16.884)	(86.743)	(91.012)	(98.655)
Reserve price	0.787***	0.969***	1.006***	0.994***
	(0.039)	(0.232)	(0.240)	(0.243)
Weak-instrument p-value		≤ 0.001	≤ 0.001	≤ 0.001
First-stage: Fraction donated(q)				
Avg. fraction donated (q)		0.808***	0.772***	0.721***
		(0.126)	(0.129)	(0.129)
Avg. reserve price		0.021	0.018	0.014
		(0.018)	(0.018)	(0.018)
Sanderson-Windmeijer F-stat		41.20	35.10	30.65
First-stage: Reserve price				
Avg. fraction donated (q)		63.549	82.065	94.156
		(59.562)	(61.162)	(58.766)
Avg. reserve price		48.464***	47.934***	46.181***
		(9.284)	(9.242)	(8.998)
Sanderson-Windmeijer F-stat		28.39	26.75	25.38
First-stage F-stat		13.679	12.508	11.756
Main variables	✓	✓	✓	✓
Add. charity dummies	✓		✓	✓
League/match dummies	✓			✓
N	1,107	1,107	1,106	1,106

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

Note: OLS and IV regressions of the transaction price on covariates. The reserve price and the fraction donated are instrumented using the (ln) average reserve price and the (ln) average fraction donated across all concurrent auctions (within ± 5 days). The middle panel reports the first stage coefficients, 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 (ln) 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 0.224, 0.258 and 0.329 respectively. The Hausman test (not reported) does not reject the null hypothesis of exogeneity of the reserve price and q at common values. The number of bidders are not included in Columns 2, 3, and 4 among the covariates because this variable is potentially endogenous (although including it does not affect the results substantially). League/Match Dummies are partialled out in Column 4. Control variables are defined in Appendix B. Robust standard errors in parentheses.

Table C4: OLS and IV regressions of the number of daily bidders on fractions donated.

Number of daily bidders (ln)	(I) OLS	(II) IV	(III) IV	(IV) IV
Fraction donated (q)	0.032	–0.016	0.120	–0.023
	(0.060)	(0.293)	(0.310)	(0.318)
Montiel-Pflueger robust p-value		$\leq$0.05	$\leq$0.05	$\leq$0.05
First-stage:				
Avg. fraction donated (q)		0.520***	0.479***	0.459***
		(0.075)	(0.073)	(0.074)
Avg. player quality (ln)		–0.081**	–0.067*	–0.070***
		(0.037)	(0.037)	(0.036)
Sanderson-Windmeijer F-stat		24.27	21.24	19.32
Over-id p-value		0.226	0.207	0.293
Main variables	✓	✓	✓	✓
Add. charity dummies	✓		✓	✓
League/match dummies	✓			✓
N	1,107	1,107	1,106	1,106

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

Note: OLS and IV regressions of the number of daily bidders (ratio of the Number of Bidders and Number of Days) on covariates (all continuous variables except q are in logs). The fraction donated is instrumented using the average fraction donated and the (ln) average player quality from the FIFA videogame across all concurrent auctions (within $\pm$5 days). The middle panel reports the first stage coefficients, 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. The reserve price and auction length are not included as covariates. Control variables are defined in Appendix B. Robust standard errors in parentheses.

Table C5: Evidence of bargaining – IV regressions

Fraction donated (q)	(I) (OLS)	(II) (IV)	(III) (OLS)	(IV) (IV)
August	0.099***	0.167***		
	(0.031)	(0.056)		
July & August			0.054**	0.147**
			(0.023)	(0.059)
Reserve price	–0.0004***	–0.0002	–0.0004***	0.0002
	(0.00007)	(0.0005)	(0.00007)	(0.0008)
Number of bidders	0.006**	0.046**	0.006***	0.074**
	(0.002)	(0.020)	(0.002)	(0.033)
Weak-instrument p-value		0.046		0.007
First-stage: Reserve price				
Avg. reserve price		0.101***		0.100***
		(0.030)		(0.031)
Avg. number of bidders		0.307		0.345
		(3.115)		(3.556)
Sanderson-Windmeijer F-stat		11.23		10.30
First-stage: Number of bidders				
Avg. reserve price		–0.0003		–0.0005
		(0.001)		(0.001)
Avg. number of bidders		0.292***		0.246***
		(0.075)		(0.079)
Sanderson-Windmeijer F-stat		15.41		9.83
Main variables	✓	✓	✓	✓
Add. charity dummies	✓	✓	✓	✓
League/match dummies	✓	✓	✓	✓
N	1,107	1,107	1,107	1,107

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

Note: OLS and IV regressions of the fraction donated on covariates. The top panel shows the coefficients of the reserve price, number of bidders, and dummy variables August (1 if the month is August and 0 otherwise) and July and August (1 if the month is either July or August and 0 otherwise). The reserve price and the number of bidders are instrumented using the average reserve price and average number of bidders across concurrent auctions within ±5 days. The middle panel reports the first stage coefficients and the Anderson-Rubin Wald test for the weak-instrument test. For over-identification (Sargan test) the average number of same team listings in past 3 weeks (±5 days) is also included as an additional instrument. The test p-value for specifications analogous to Columns 2 and 4 are 0.385 and 0.601 respectively. League/Match Dummies are partialled out in Columns 2 and 4. Unlike Table 4, the table does not include the variable Number of Bids Placed. Adding charity fixed effects does not change the coefficient estimates considerably. Control variables are defined in Appendix B. Robust standard errors in parentheses.

Table C6: Nationalities of the top bidders

	Italy	UK	France	Other EU	North Am.	China	Asia	East Asia	Other	Total
Winner	559	74	41	119	62	130	35	28	59	1107
	50.5%	6.68%	3.7%	10.75%	5.6%	11.74%	3.16%	2.53%	5.33%	–
Second	602	79	28	113	51	117	33	26	58	1107
	54.38%	7.14%	2.53%	10.21%	4.61%	10.57%	2.98%	2.35%	5.24%	–
Total	1,161	153	69	232	113	247	68	54	117	–

Note: Nationalities of the top bidders by geographic area. "Other" includes also unknown nationalities.

Table C7: Transaction prices and nationality of the winning bidders

Transaction price	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Fraction donated (q)	67.951***	67.983***	69.163***	68.277***	67.728***	67.985***	67.822***
	(19.884)	(19.925)	(19.876)	(19.882)	(19.929)	(19.861)	(19.818)
Win: Italy	0.605						
	(8.857)						
Win: UK		0.754					
		(15.930)					
Win: France			–19.570				
			(19.434)				
Win: Other EU				11.758			
				(13.359)			
Win: North America					27.336		
					(17.566)		
Win: China						0.528	
						(14.092)	
Win: Asia							–33.856*
							(20.428)
Main variables	✓	✓	✓	✓	✓	✓	✓
Add. charity dummies	✓	✓	✓	✓	✓	✓	✓
League/match dummies	✓	✓	✓	✓	✓	✓	✓
Time dummies	✓	✓	✓	✓	✓	✓	✓
Charity fixed effects	✓	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.574	0.574	0.575	0.575	0.575	0.574	0.575
N	1,107	1,107	1,107	1,107	1,107	1,107	1,107

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

Note: OLS regressions of the transaction price on covariates including dummies for the most common nationalities of the winning bidder. All regressions include the number of bidders, and the reserve price (not shown); the remaining control variables are defined in Appendix B. Robust standard errors in parenthesis.

Table C8: Transaction prices and recurrent winners

Transaction price	(I)	(II)	(III)	(IV)
Fraction donated (q)	107.586***	108.344***	64.508***	67.746***
	(17.509)	(19.943)	(19.660)	(21.969)
Recurrent winner	11.852	13.175	12.958	18.344
	(8.138)	(18.610)	(8.127)	(20.045)
Recurrent winner · fraction donated (q)		–1.870		–7.590
		(25.959)		(27.546)
Marginal effect of recurrent winner		11.305		10.754
		(12.150)		(12.213)
Main variables	✓	✓	✓	✓
Add. charity dummies			✓	✓
League/match dummies			✓	✓
Time dummies	✓	✓	✓	✓
Charity fixed effects			✓	✓
Adjusted R-squared	0.564	0.563	0.616	0.616
N	1,107	1,107	1,107	1,107

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

Note: 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) and 0 otherwise. The variable "recurrent winner" is interacted with the fraction donated in even columns. The effect of recurrent winner on transaction prices is negligible ($\sim$ 3% of transaction prices) on average. The second panel shows that the marginal effect of "recurrent winner" when interacted with the fraction donated is not significantly different from zero (even columns). Therefore, the slope of the transaction price in auctions won by potential collectors is not different compared to auctions won by other bidders. All regressions include the number of bidders, the reserve price and the interactions of the reserve price with the number of bidders and jersey characteristics; the remaining control variables are defined in Appendix B. Robust standard errors in parenthesis.

Table C9: Overview of the most common models of altruism

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 shill ($\alpha > \beta > 0$)	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 Section 3.2 for more information. Source: Leszczyc and Rothkopf (2010).

Table C10: First step of the structural estimation

Transaction price (ln)	OLS regression (I)		OLS regression (II)	IV regression (III)		IV regression (IV)
Reserve price (ln)	0.361	***	(0.025)	0.402	***	(0.096)
Minimum raise (ln)	0.100	***	(0.037)	0.102	***	(0.038)
Sold at reserve price (0/1)	−0.137	***	(0.048)	−0.160	**	(0.068)
Number of bidders (ln)	0.313	***	(0.035)	0.313	***	(0.035)
Length (ln)	0.069		(0.068)	0.077		(0.070)
Extended time (0/1)	0.075	**	(0.031)	0.074	**	(0.031)
Length of description (ln)	0.039		(0.024)	0.035		(0.026)
Content in English (0/1)	−0.042		(0.038)	−0.047		(0.040)
Length of charity description (ln)	−0.049	*	(0.029)	−0.050	*	(0.029)
Number of pictures (ln)	−0.008		(0.034)	−0.010		(0.035)
Number of same team auctions in past 3 weeks (ln)	0.094	***	(0.024)	0.094	***	(0.024)
Number of same player auctions in past 2 weeks (ln)	0.078	***	(0.017)	0.076	***	(0.018)
Counter of auctions from same charity (ln)	−0.056	***	(0.015)	−0.058	***	(0.016)
Player belongs to FIFA 100 list (0/1)	0.143	***	(0.055)	0.135	**	(0.057)
Fifa 16 overall player quality (0/1)	0.004		(0.011)	0.005		(0.011)
Jersey is unwashed (0/1)	0.232	***	(0.051)	0.225	***	(0.052)
Jersey is signed (0/1)	0.057		(0.047)	0.070		(0.057)
Jersey is signed by team players/coach (0/1)	0.118		(0.074)	0.138		(0.087)
Jersey is worn (0/1)	−0.016		(0.052)	−0.020		(0.053)
Jersey is worn during a final (0/1)	0.329	***	(0.100)	0.314	***	(0.108)
Number of goals scored	0.181	***	(0.068)	0.171	**	(0.071)
Jersey belongs to an important team (0/1)	0.206	***	(0.049)	0.194	***	(0.054)
Charity is English (0/1)	−0.034		(0.078)	−0.051		(0.087)
Charity deals with disabilities (0/1)	0.116	***	(0.039)	0.122	***	(0.042)
Charity builds infrastructures in developing countries (0/1)	0.186	**	(0.075)	0.186	**	(0.075)
Charity deals in healthcare (0/1)	−0.167	***	(0.059)	−0.164	***	(0.061)
Charity has humanitarian scopes in developing countries (0/1)	0.080		(0.074)	0.072		(0.078)
Charity deals with children's wellbeing (0/1)	0.072		(0.066)	0.071		(0.067)
Charity deals with neurodegenerative disorders (0/1)	0.115		(0.091)	0.099		(0.095)
Charity linked to a soocer team (0/1)	−0.205	**	(0.090)	−0.212	**	(0.093)
Charity aims to improve access to sport (0/1)	−0.006		(0.073)	−0.002		(0.074)
Constant	2.910	***	(0.303)	2.728	***	(0.523)
Weak instruments (F-test)				22.589		
Over-id test (p-value)				0.784		
Adjusted R-squared	0.460			0.458		
N	728			728		

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

Note: OLS and IV regressions of the logarithm of the transaction price as in the first step of the structural model. The reserve price is instrumented with the average reserve price (ln) and the average auction length (ln) in concurrent auctions (±5 days) in Columns 3 and 4. The Hausman test p-value is 0.728. The symbol (0/1) indicates dummy variables. Control variables are defined in Appendix B. Robust standard errors in parenthesis in even columns.

Table C11: Estimated altruistic demand parameters with instruments

Number of bidders Quantile	n	α [95% CI]	β [95% CI]
99%	16	0.242	0.519
		[0.123, 0.356]	[0.229, 0.680]
95	14	0.239	0.518
		[0.122, 0.352]	[0.228, 0.679]
90	12	0.235	0.518
		[0.120, 0.346]	[0.228, 0.678]
75	10	0.230	0.517
		[0.117, 0.338]	[0.227, 0.676]
50	7	0.215	0.514
		[0.111, 0.317]	[0.225, 0.673]

Note: The results of 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 auction length in concurrent auctions (± 5 days). Column 2 of Appendix Table C10 reports the coefficient estimates from the first-step IV regression. The F-test is 22.589, and the over-identification test statistics (Sargan test) has a p-value of 0.784. The preference parameters α and β represent the additional utility stemming from other individuals' donations and the bidder's own donations, respectively. 95% bootstrap confidence intervals are in square brackets (401 repetitions). The dataset includes only auctions where $q \in \{10\%, 85\%\}$.

Table C12: Correlation between the fraction donated on the number of auctions

Avg. weekly number of auctions	(I)	(II)	(III)
Avgerage q (weekly)	1.079	0.960	0.193
	(10.855)	(10.744)	(10.524)
Lagged number of auctions (weekly)	0.122	0.121	0.120
	(0.116)	(0.118)	(0.120)
Avgerage q (weekly), lag 1 week		4.581	4.548
		(10.726)	(10.752)
Avgerage q (weekly), lag 2 weeks			3.109
			(10.116)
Linear combination of $\bar{q}$ and its lags (p-value)		0.741	0.698
Adjusted R-squared	0.413	0.410	0.405
N	173	173	172

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

Note: OLS regressions of the weekly number of auctions on past fractions donated. The dataset includes all auctions of sold jerseys between July 1st, 2015, and November 8th, 2018. All regressions include month and year fixed effects. The variance inflation factor (vif) is alwasy below 2.75. Robust standard errors in parentheses. The qualitative results would not change if standard errors were clustered at the level of month and year. Similar results also hold (unreported) if the dataset is collapsed by months instead of weeks.

Table C13: Correlation between the fraction donated and the number of bidders

	Independent variables					
	Lagged dep. var.	Avg. q (week)	Avg. q (lag 1)	Avg. q (lag 2)	Adj. R-sq.	N
Dependent variable: Average number of bidders (weekly)						
Average num. bidders	0.186**	0.024			0.174	173
	(0.086)	(0.906)				
Average num. bidders	0.186**	–0.007	1.248		0.179	173
	(0.084)	(0.936)	(0.936)			
Average num. bidders	0.191**	0.172	1.254	–0.790	0.176	172
	(0.087)	(0.948)	(0.943)	(1.096)		
Dependent variable: Median number of bidders (weekly)						
Q(50%) num. bidders	0.214**	0.148			0.121	173
	(0.091)	(1.041)				
Q(50%) num. bidders	0.214**	0.135	0.652		0.118	173
	(0.090)	(1.047)	(1.137)			
Q(50%) num. bidders	0.215**	0.463	0.661	–1.380	0.122	172
	(0.089)	(1.105)	(1.145)	(1.248)		
Dependent variable: 9^{th} decile of the number of bidders (weekly)						
Q(90%) num. bidders	0.087	–1.433			0.134	173
	(0.095)	(1.594)				
Q(90%) num. bidders	0.093	–1.491	1.346		0.132	173
	(0.094)	(1.588)	(1.732)			
Q(90%) num. bidders	0.084	–1.533	1.360	0.527	0.125	172
	(0.095)	(1.712)	(1.749)	(2.116)		

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

Note: OLS regressions of the weekly number of bidders on past fractions donated. The dependent variable varies across rows, while the independent variables vary across columns. The lagged dependent variable is in column 1. The dataset includes all auctions of sold jerseys between July 1st, 2015, and November 8th, 2018. All regressions include month and year fixed effects. Robust standard errors in parentheses. The qualitative results would not change if standard errors were clustered at the level of month and year. Similar results also hold (unreported) if the dataset is collapsed by months instead of weeks.

C.1 The Impact of VC Entry

This section exploits a change in Charitystars's capital structure to corroborate the previous evidence that the firm's objectives extend beyond profitability. In April 2017, a group of investors, including a venture capital (VC) fund, purchased a share of Charitystars's equity.[10] The different investment horizon of the VC fund compared to that of the founders advances the thesis that this entry altered the firm's objectives toward profitability. The dataset used for this analysis includes all soccer jersey auctions concluded before November 2018 to study how the entry of the VC fund affected the firm's fractions donated (q), net revenues, numbers of auctions and bidders, and procurement costs.[11]

Fraction donated. Figure 6 in the main text plots the average fraction donated by quarter. The average q was consistently greater than 0.65 in the pre-entry period but decreased sharply after the entry, reaching values between 0.25 and 0.30 by the end of 2018. In particular, the average fraction donated is 0.70 before the entry, but only 0.52 after the entry (one-sided p-value $< 0.1\%$); this is the first evidence of a change in strategy. To control for whether the lower q is due to lower quality items being auctioned, Table C14 regresses q on a post-entry dummy, $post_t$, which is 1 for auctions concluded since May 2017, and covariates as follows:

$$q_t = \theta_0 + \theta_{post} \cdot post_t + \mathbf{x}_t \theta + FE_t + \varepsilon_t, \tag{C.1}$$

where t indexes auctions. All the columns include controls for week and charity fixed effects, as well as for listing, jersey, team and match characteristics.[12] Columns 3 and 4 also include the reserve price, the number of bidders, and the number of bids placed. The last two variables account for the potential differences in bargaining power that arise when a provider has a high quality item, as the fiercer competition for these items could imply more bids per bidder than otherwise. Finally, since the reserve price and q are simultaneously determined and the expected number of bidders could influence the choice of q, the last two columns instrument these two variables using the outcomes of concurrent auctions. Across the columns, the coefficient $\hat{\theta}_{post}$ is always smaller than -0.32, statistically significant and

[10] The equity stake and its price are not disclosed.

[11] The firm introduced several changes since June 2017, such as a new website layout and new payment mechanisms (e.g., bitcoins and changes to minimum raises). Since the exact dates of each of these changes are unknown, the flexibility of the reduced form analyses above is superior to applying the structural approach from earlier sections to the whole sample.

[12] To highlight that sample selection does not affect the results, the even columns in the tables in this section lift the restrictions on prices (in €100 - €1,000) and q (≤ 0.85). More details are in the note under the tables.

unaffected by the different controls, reflecting a substantial drop in q after the entry.[13]

Net revenues. Consistent with the warm glow model of bidding identified in Section 3.4.1 in the main text, bidders' willingness to pay declined as a result of the decrease in fractions donated, which lowered transaction prices from an average value of €478 before the entry to only €370 in the post-entry period (one-sided p-value $< 0.1\%$). However, the lower q more than compensated for this change in transaction prices. Disregarding the transition period by omitting the auctions within one year of the VC entry, the net average revenues before June 2016 were only €156, but they reached €241 from June 2018 onward (one-sided p-value $< 0.1\%$).[14]

Auctions and bidders. Despite the decrease in q, the VC entry did not affect the number of bidders. Table C17 shows the estimates of Poisson and IV regressions analogous to Equation C.1 with the number of bidders as the dependent variable and auction length as the exposure variable. The last two columns instrument the reserve price and the fraction donated as previously done. The results show a slight although economically negligible increase of 0.2 bidders per auction after the entry. Moreover, the number of auctions increased to above 25 per week after the entry from an average value of 16 before the entry.

Procurement costs. The supply-side estimates suggest that a lower fraction donated implies higher procurement costs. To assess whether the bargaining paradigm changed after the entry of the VC fund, let us modify regression C.1 by using the imputed costs, $(1 - q) \cdot \textit{Reserve price}$, as dependent variable, and with the fraction donated in $\mathbf{x}_t$ instead of the reserve price. Table C16 estimate this regression equation by OLS (Columns 1 to 4) and also using outcomes from concurrent auctions as instruments to account for the simultaneity in q and reserve prices as previously done (Columns 5 and 6). Across all columns, $\hat{\theta}_{post}$ is negative and significant, implying lower costs between €44 and €130.

[13] The whole distribution shifted leftward after the entry of the VC fund, as shown in Appendix Table C15 which regresses each decile of the weekly average fraction donated on the post-entry dummy.

[14] This fork expands further if we only consider the most common auctions (price in €100 - €1,000 and $q \leq 0.85$). The average net revenues are only €93 before June 2016 and they increase to €218 after June 2018 (one-sided p-value: $< 0.1\%$). Including the period around the VC entry instead, net revenues increased from €156 to €183 on average on the whole sample (one-sided p-value: 0.009%)

Table C14: Fractions donated and the entry of the the VC fund

	OLS				IV regressions	
Fraction donated (q)	(I)	(II)	(III)	(IV)	(V)	(VI)
Post entry (0/1)	–0.352***	–0.328***	–0.579***	–0.348***	–0.331***	–0.380***
	(0.108)	(0.059)	(0.087)	(0.059)	(0.124)	(0.067)
Reserve price			–0.001***	–0.000***	0.000	–0.000**
			(0.000)	(0.000)	(0.001)	(0.000)
Number of bidders			–0.002	0.000	0.018**	0.015**
			(0.002)	(0.001)	(0.008)	(0.006)
Number of bids placed			0.001**	0.001**		
			(0.000)	(0.000)		
Weak-instrument p-value					0.081	0.025
First-stage: Reserve price						
Avg. reserve price (ln)					–59.124***	–433.733***
					(19.173)	(128.692)
Avg. number of bidders (ln)					–9.651	155.687*
					(33.961)	(93.915)
Sanderson-Windmeijer F-stat					9.85	11.64
First-stage: Number of bidders						
Avg. reserve price (ln)					0.538	–0.409
					(0.368)	(0.449)
Avg. number of bidders (ln)					–9.189***	–9.896***
					(0.991)	(0.963)
Sanderson-Windmeijer F-stat					82.85	115.10
Charity fixed effect	✓	✓	✓	✓	✓	✓
Week fixed effect	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Subset:						
Price range (euro)	(100,1,000)	all	(100,1,000)	all	(100,1,000)	all
q range	≤ 0.85	all	≤ 0.85	all	≤ 0.85	all
N	3,360	4,271	3,360	4,271	3,360	4,271

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

Note: 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 dataset includes all auctions of sold jerseys between July 1st, 2015, and November 8th, 2018. The second panel reports the first stage statistics from the IV regressions (Columns 5 and 6), where the reserve price and the number of bidders are instrumented with the average reserve price (ln) and the average number of bidders (ln) in concurrent auctions (± 5 days). The weak-instrument p-value refers to the Anderson-Rubin Wald Test. The average number of worn jerseys in concurrent auctions is used for overidentification (unreported Sargan test p-values are 0.289 and 0.261 in Columns 5 and 6). The third panel indicates the controls used in each regression."Additional controls" include dummies indicating whether the auction listing states that the match or jersey refers to the Champions League, the Europa League, the Italian Serie A, the English Premier League, the Spanish Liga, the German Bundesliga, the World Cup, a final, a worn jersey, a signed jersey, and an unwashed jersey, as well as variables for the minimum raise, the length (in days) of the auction (computed from the first bid), the number of pictures displayed on the website, the length of the item description (in words), the length of the charity description (in words), and whether the auction time was extended due to a bid in the last 4 minutes. The fourth panel indicates the relevant subset where each regression is performed. Since the average variance of the fraction donated within a charity is close to zero, the table reports robust standard errors in parenthesis, but the qualitative results would not change if the standard errors were clustered by charity.

Table C15: Distribution of the weekly fractions donated

Decile of weekly q	(I) 10^{th}	(II) 20^{th}	(III) 30^{th}	(IV) 40^{th}	(V) 50^{th}	(VI) 60^{th}	(VII) 70^{th}	(VIII) 80^{th}	(IX) 90^{th}
Post entry (0/1)	-0.136^{***}	-0.260^{***}	-0.298^{***}	-0.273^{***}	-0.261^{***}	-0.188^{***}	-0.084^{***}	-0.043^{***}	-0.027^{***}
	(0.045)	(0.050)	(0.051)	(0.049)	(0.043)	(0.038)	(0.022)	(0.014)	(0.010)
Month fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.115	0.132	0.153	0.157	0.183	0.144	0.072	0.038	0.061
N	174	174	174	174	174	174	174	174	174

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

Note: OLS regressions of different quantiles of the weekly fraction donated on a dummy for the post-VC entry period. The variable "post entry" is 1 for the period from June 1^{st}, 2017 onwards, and 0 otherwise. The data includes all auctions of sold jerseys between July 1^{st}, 2015, and November 8^{th}, 2018. Robust standard errors in parenthesis. The qualitative results would not change if the standard errors were clustered at the level of month and year. Similar results also hold (unreported) if the dataset is collapsed by months instead of weeks.

Table C16: Procurement costs and the entry of the the VC fund

	OLS				IV regressions	
Procurement cost	(I)	(II)	(III)	(IV)	(V)	(VI)
Post entry (0/1)	20.549	–12.323	–62.451***	–129.832***	–42.453*	–116.955*
	(34.183)	(44.129)	(23.644)	(49.574)	(24.900)	(66.789)
Fraction donated (q)			–228.110***	–302.281***	–178.810***	–318.877**
			(8.275)	(17.710)	(27.859)	(129.908)
Number of bidders			1.919***	6.440**		
			(0.650)	(2.960)		
Number of bids placed			–0.548***	–0.515		
			(0.126)	(0.345)		
Montiel-Pflueger robust test p-value					≤ 0.05	≤ 0.05
First-stage for fraction donated (q):						
Avg. fraction donated (q)					–1.150***	–1.147***
					(0.103)	(0.088)
Avg. number of unwashed jerseys					0.502***	0.666**
					(0.125)	(0.104)
Sanderson-Windmeijer F-stat					63.92	89.75
Over-id p-value					0.346	0.627
Charity fixed effect	✓	✓	✓	✓	✓	✓
Week fixed effect	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Subset:						
Price range (euro)	(100,1,000)	all	(100,1,000)	all	(100,1,000)	all
q range	≤ 0.85	all	≤ 0.85	all	≤ 0.85	all
N	3,360	4,271	3,360	4,271	3,360	4,271

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

Note: OLS and IV regressions of the procurement cost on covariates. The variable "post entry" is 1 for the period from June 1st, 2017 onwards, and 0 otherwise. The dataset includes all auctions of sold jerseys between July 1st, 2015, and November 8th, 2018. The second panel reports the first stage statistics from the IV regressions (Columns 5 and 6), where the fraction donated (q) is instrumented with the average fraction donated and the average number of unwashed jerseys in concurrent auctions (± 5 days). The third panel indicates the controls used in each regression."Additional controls" include dummies indicating whether the auction listing states that the match or jersey refers to the Champions League, the Europa League, the Italian Serie A, the English Premier League, the Spanish Liga, the German Bundesliga, the World Cup, a final, a worn jersey, a signed jersey, and an unwashed jersey, as well as variables for the minimum raise, the length (in days) of the auction (computed from the first bid), the number of pictures displayed on the website, the length of the item description (in words), the length of the charity description (in words), and whether the auction time was extended due to a bid in the last 4 minutes. The fourth panel indicates the relevant subset where each regression is performed. The results do not change substantially if the clustering is done at the charity or at the year level. Since the average variance of the fraction donated within a charity is close to zero, the table reports robust standard errors in parenthesis, but the qualitative results would not change if the standard errors were clustered by charity.

Table C17: Number of bidders and the entry of the the VC fund

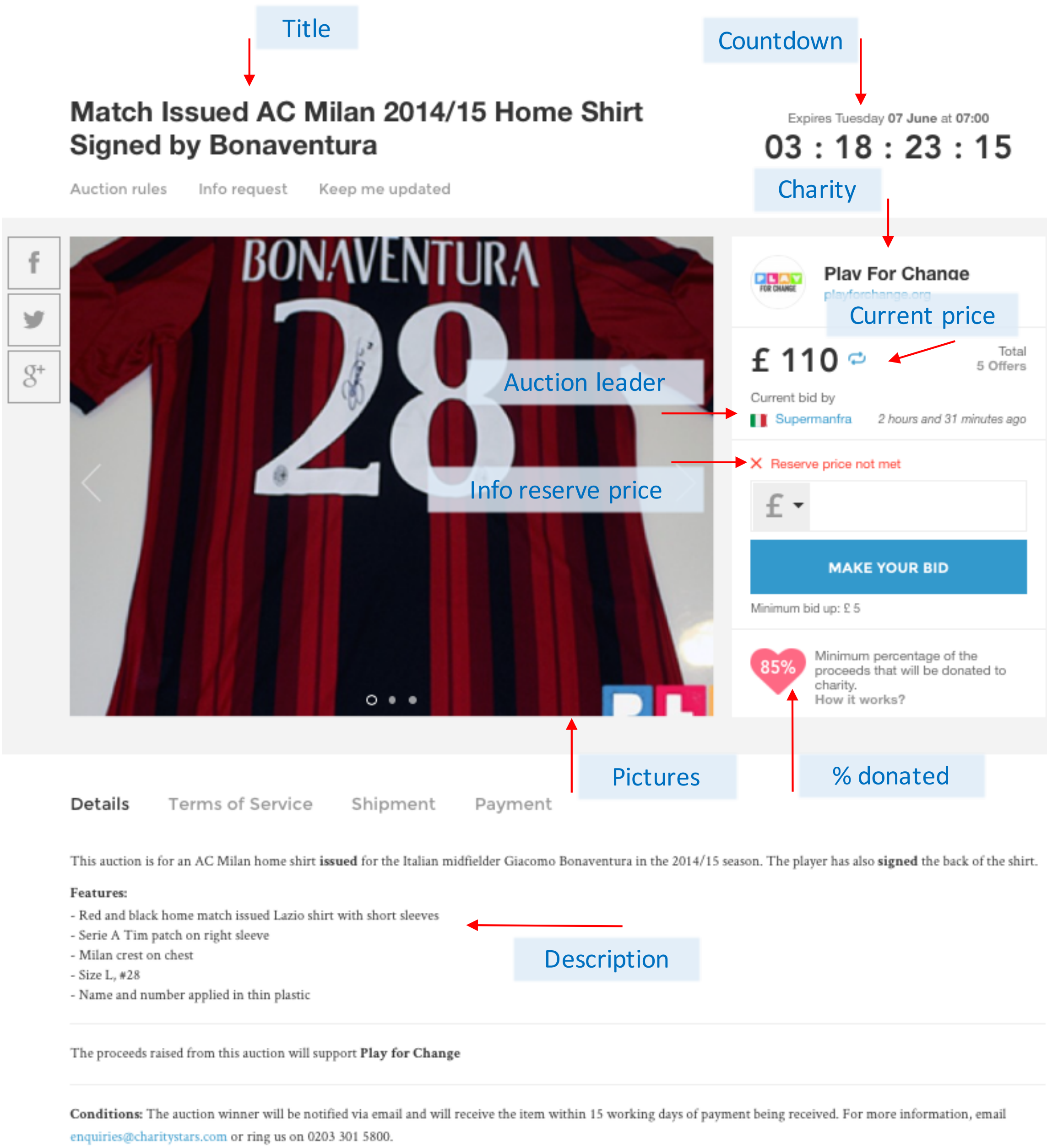
	Poisson regressions				IV regressions	
Number of daily bidders	(I)	(II)	(III)	(IV)	(V)	(VI)
Post entry (0/1)	0.072	0.341	0.085	0.348	0.075	0.266
	(0.178)	(0.271)	(0.179)	(0.271)	(0.227)	(0.240)
Fraction donated (q)			0.035	0.005	–0.033	–0.013
			(0.031)	(0.032)	(0.167)	(0.168)
Reserve price			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.001)	(0.000)
Weak-instrument p-value					0.945	0.320
First-stage: Fraction donated (q)						
Avg. fraction donated (q)					–1.216***	–1.157***
					(0.105)	(0.090)
Avg. reserve price (ln)					–0.121***	–0.069***
					(0.033)	(0.026)
Sanderson-Windmeijer F-stat					103.73	160.52
First-stage: Reserve price						
Avg. fraction donated (q)					–18.678	–217.593**
					(47.520)	(98.381)
Avg. Reserve price (ln)					–61.560***	–446.187***
					(19.797)	(125.296)
Sanderson-Windmeijer F-stat					9.86	15.34
Charity fixed effect	✓	✓	✓	✓	✓	✓
Week fixed effect	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Subset:						
Price range (euro)	(100,1,000)	all	(100,1,000)	all	(100,1,000)	all
q range	≤ 0.85	all	≤ 0.85	all	≤ 0.85	all
N	3,360	4,271	3,360	4,271	3,360	4,271

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

Note: Columns 1 to 4 report poisson regressions of the number of bidders on covariates with auction length (plus one day) as the exposure variable, while Columns 5 and 6 show IV regressions of the log of the ratio between the number of bidders and the auction length (plust one day) on covariates. The variable "post entry" is 1 for the period from June 1st, 2017 onwards, and 0 otherwise. The dataset includes all auctions of sold jerseys between July 1st, 2015, and November 8th, 2018. The second panel reports the first stage statistics from the IV regressions, where the fraction donated (q) and the reserve price are instrumented with the fraction donated and reserve price (ln) in concurrent auctions ($\pm$5 days). The weak-instrument p-value refers to the Anderson-Rubin Wald Test. The average number of item pictures displayed in concurrent listings is used for overidentification (unreported Sargan test p-values are 0.144 and 0.189 in Columns 5 and 6). The third panel indicates the controls used in each regression."Additional controls" include dummies indicating whether the auction listing states that the match or jersey refers to the Champions League, the Europa League, the Italian Serie A, the English Premier League, the Spanish Liga, the German Bundesliga, the World Cup, a final, a worn jersey, a signed jersey, and an unwashed jersey, as well as variables for the minimum raise, the number of pictures displayed on the website, the length of the item description (in words), the length of the charity description (in words), and whether the auction time was extended due to a bid in the last 4 minutes. The fourth panel indicates the relevant subset where each regression is performed. Since the average variance of the fraction donated within a charity is close to zero, the table reports robust standard errors in parenthesis, but the qualitative results would not change if the standard errors were clustered by charity.

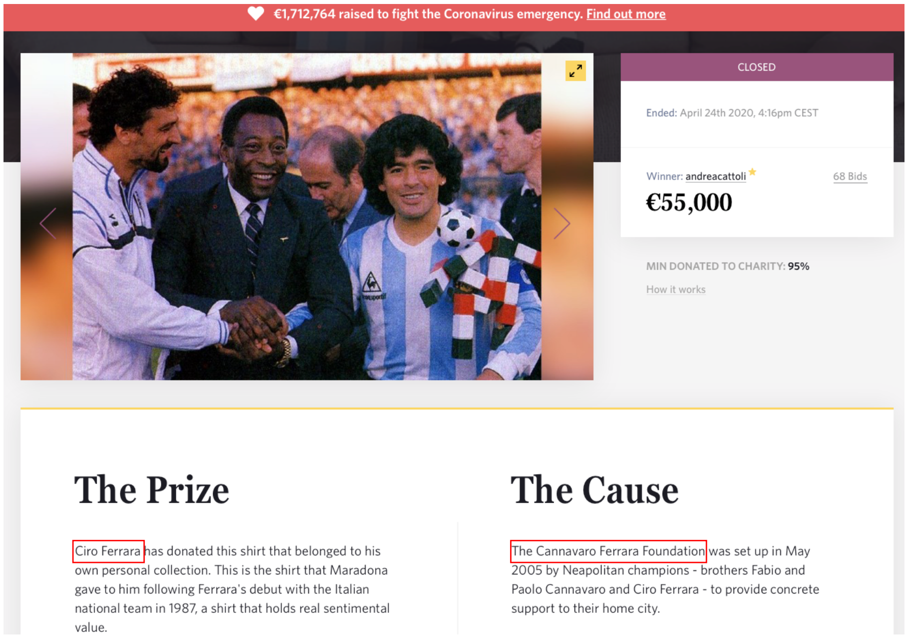
D Omitted Figures

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



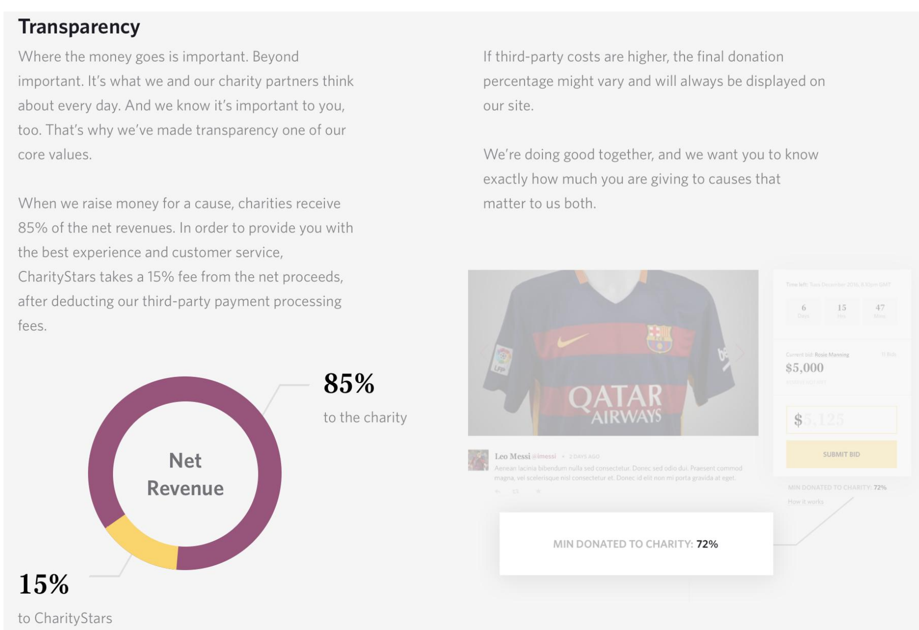
Note: Screenshot of a webpage of a running auction on Charitystars.com for an AC Milan jersey worn and signed by the player Giacomo Bonaventura. The standing price is GBP 110: this bid was placed by an Italian bidder with username "Supermanfra". At the time of the screenshot, a total of five bids were already placed. 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". Accessed on June 3rd, 2016.

Figure D2: Provider of the item and charity



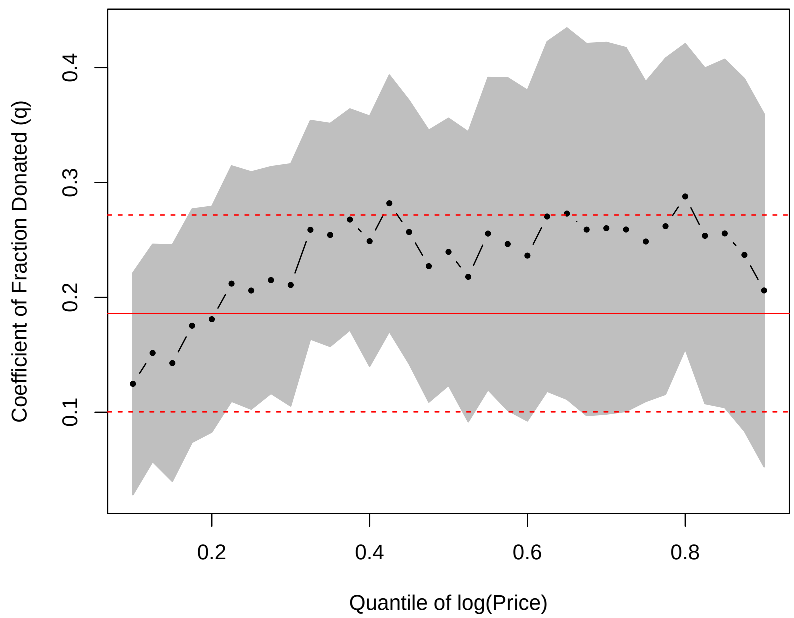
Note: Screenshot of a webpage of an auction on Charitystars.com. The text indicates that the provider of the item, Ciro Ferrara, is closely linked with the charity receiving the donation, the *Cannavaro Ferrara Foundation*. Accessed on May 5th, 2020.

Figure D3: How the firm allocates the funds



Note: Screenshot describing how the firm allocates the fraction donated. Accessed November 7th, 2018.

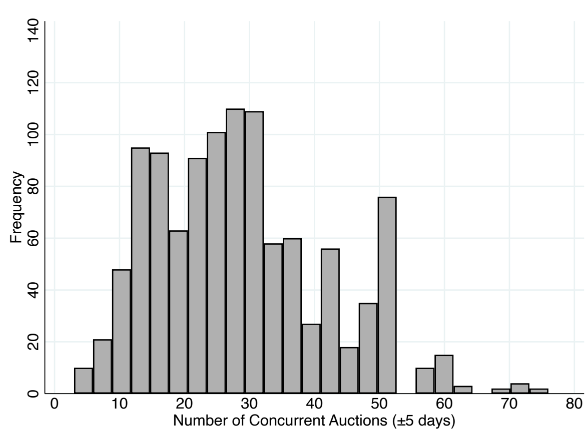
Figure D4: Quantile regression of the log of transaction price on q



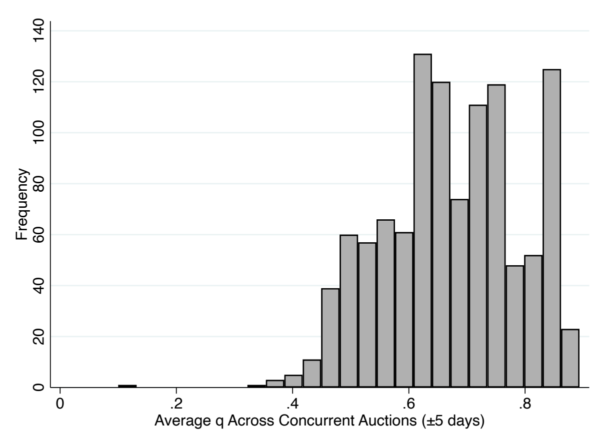
Note: The coefficients from quantile regressions of the logarithm of the transaction price on q and covariates. The dashed (dotted) line shows the coefficient of the OLS regression (5% confidence interval). Appendix Table C1 shows the coefficients for each quartile. Boostrapped standard errors with 400 repetitions.

Figure D5: Frequency of concurrent auctions ($\pm$5 days) used as instrument

(a) Number of concurrent auctions

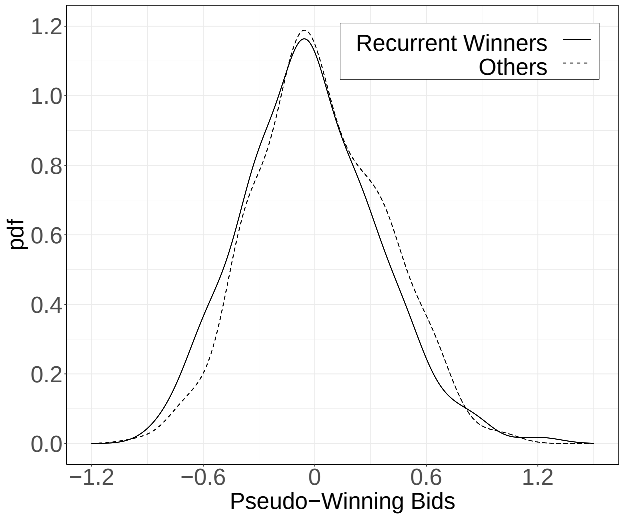


(b) Avg. fraction donated in concurrent auctions



Note: Panel a. The y-axis reports how many listings have the number of concurrent auctions shown in the x-axis. The 1^{st} percentile is 6, the 10^{th} is 12, the median is 27, the 90^{th} is 50 and the 99^{th} is 60. Panel b. Histogram of the average fraction donated across concurrent auctions. The 1^{st} percentile is 0.428, the 10^{th} is 0.501, the median is 0.670, the 90^{th} is 0.850 and the 99^{th} is 0.872. In both panels, auctions are "concurrent" if they happen within $\pm$5 days of the end of an auction. Concurrent auctions include all auctions for soccer jerseys available in the dataset (1,580 auctions).

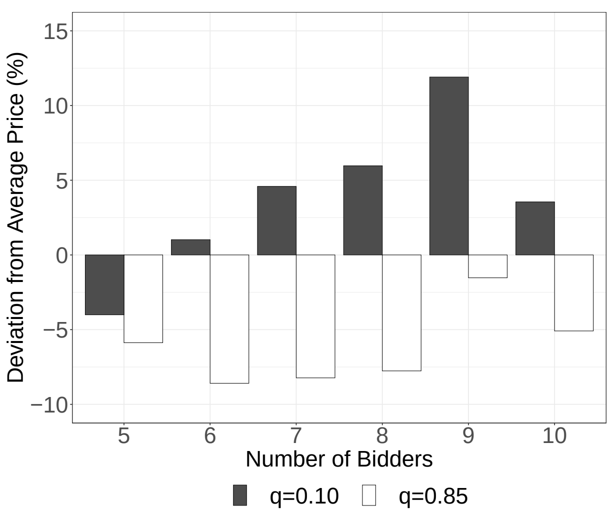
Figure D6: Densities of the pseudo winning bids of recurrent winners and other winners



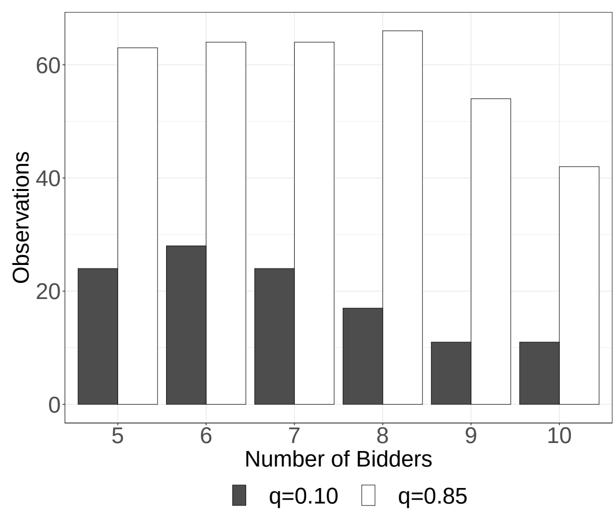
Note: Comparison of the densities of the pseudo winning bids from the first-step of the structural model for recurrent winners (i.e., winners who won more than 3 auctions) and other winners. The Kolmogorov-Smirnov test does not reject the null hypothesis that the two densities are equal at the 0.298 level. The first-stage regression (3.6) includes main variables, league/match dummies, time dummies and, analogous to Appendix Table C8, also interactions between the reserve price (ln) and jersey characteristics. The plotted densities are computed using a Gaussian kernel and Silverman's rule-of-thumb bandwidths (Silverman, 1986).

Figure D7: Comparison between the model implied prices and observed average prices

(a) Deviation from average price (%)

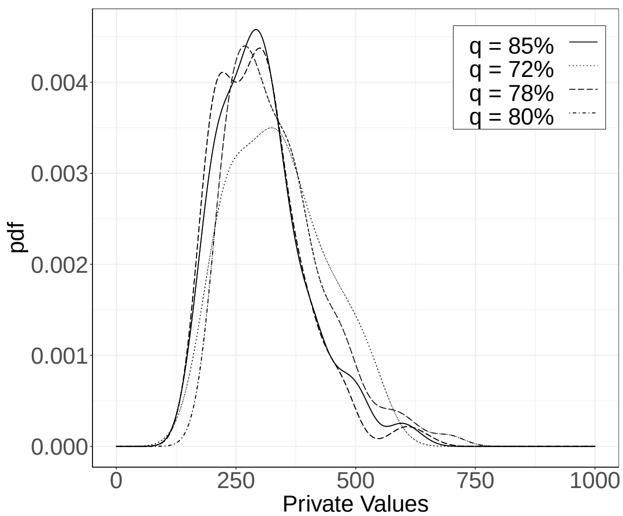


(b) Observations per number of bidders



Note: Panel a. The percentage difference between the observed price in the data and the expected price implied by the model for different number of bidders and fractions donated. A positive number indicates that the model overstates prices. Across scenarios, the null hypothesis that the average observed and implied prices are equal is never rejected at the standard confidence levels. For $q = 0.1$, the t-test p-values are 0.73 (5 bidders), 0.94, 0.74, 0.70, 0.55 and 0.83 (10 bidders). Similarly, for $q = 0.85$, the p-values are 0.34, 0.22, 0.32, 0.27, 0.84, 0.57. Panel b. The number of auctions available such that the number of bidders is equal to that displayed on the x axis, whose range is the IQR of the number of bidders.

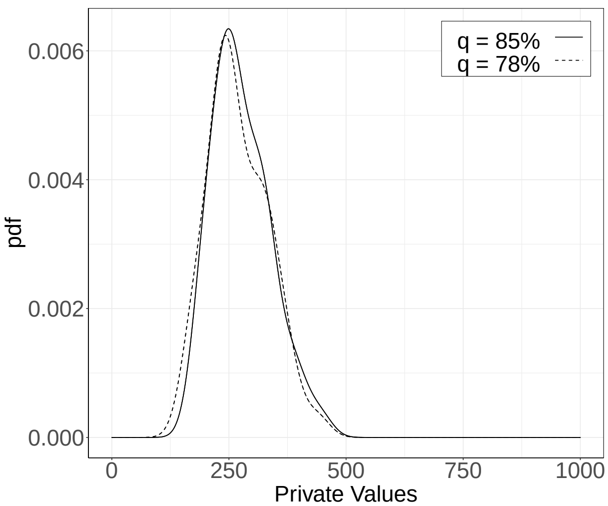
Figure D8: Out-of-sample validation with three auxiliary datasets



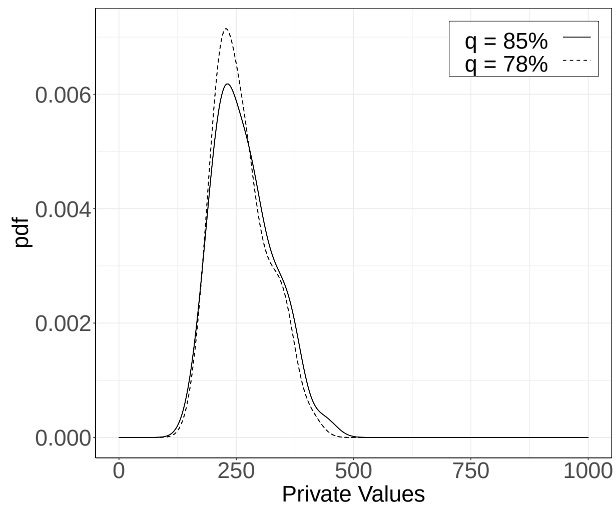
Note: Comparison of the densities of the private values estimated from the structural model employing data from auctions with $q = \{10\%, 85\%\}$ and the density of the private values obtained projecting the three-step estimation procedure on the $q = 72\%$ auctions (dotted line), the $q = 78\%$ auctions (dashed line), and the $q = 80\%$ auctions (dot-dashed line). The null hypothesis (equality) cannot be rejected at the 0.170, 0.845 and 0.118 level. 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 D9: Out-of-sample test on demand estimates computed on subsets of auctions with the similar number of bidders

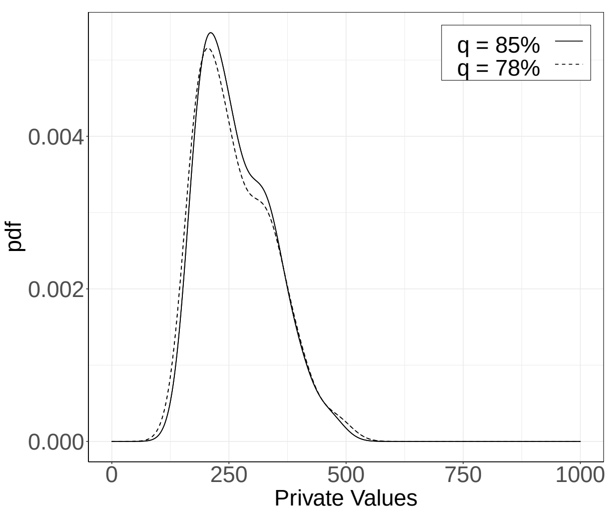
(a) 5 & 6 bidders, $\hat{\alpha} = 0.153, \hat{\beta} = 0.478$



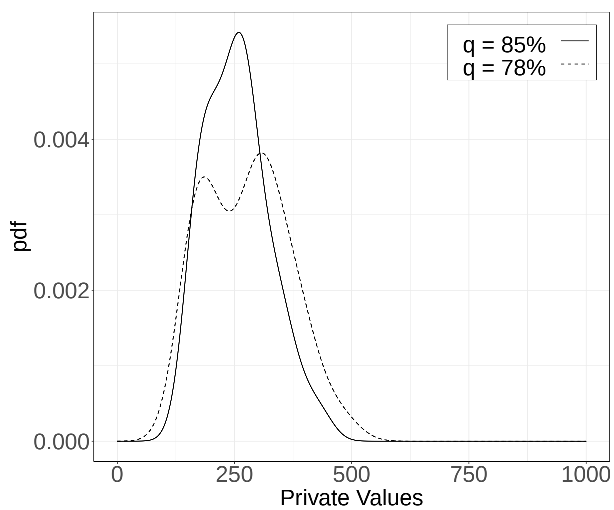
(b) 6 & 7 bidders, $\hat{\alpha} = 0.212, \hat{\beta} = 0.466$



(c) 7 & 8 bidders, $\hat{\alpha} = 0.336, \hat{\beta} = 0.498$



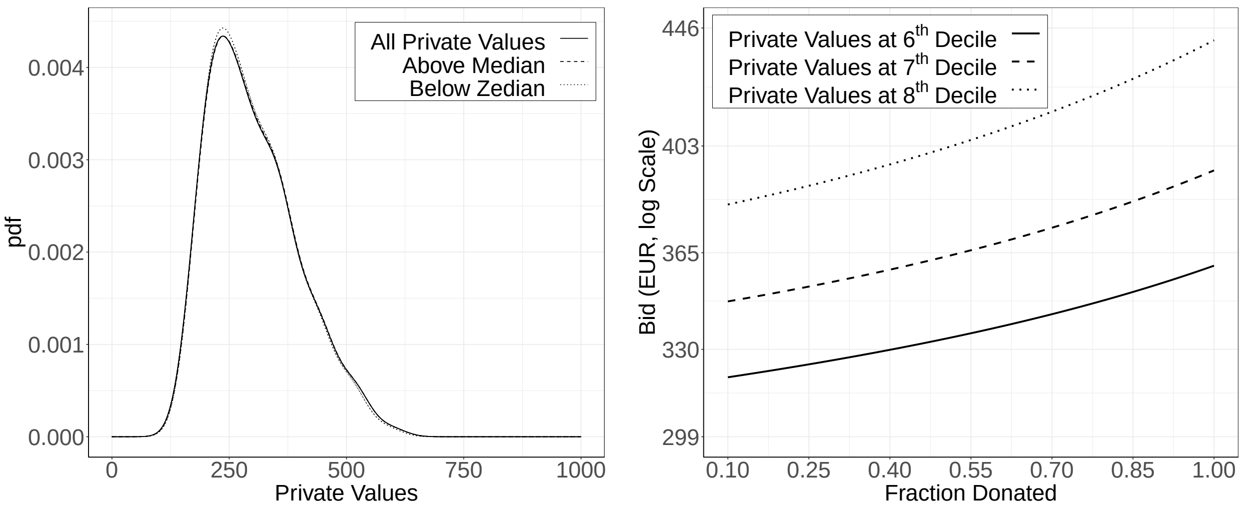
(d) 8 & 9 bidders, $\hat{\alpha} = 0.411, \hat{\beta} = 0.580$



Note: Each plot refers to a different estimation of the demand primitives based on subsets of the data according to the number of bidders specified in the caption. The variable "number of bidders" is not included in the first-stage regression (3.6). The reserve price is instrumented with the average reserve price and the average auction length across concurrent auctions (OLS regressions produce similar results). For Panels a, b and c the estimated $(\hat{\alpha}, \hat{\beta})$ are in the 95% C.I. show in Appendix Table C11, while they are in the 99% C.I. for Panel d for which less observations are available. The average α and β across samples are 0.271 and 0.485, which are very close to the main estimates in Table 3 ($\alpha = 0.227$ and $\beta = 0.490$). The Kolmorov-Smirnov test does not reject the null that the in-sample and out-of-sample densities are the same at the 0.952 level in Panel a, at the 0.853 level in Panel b, at the 0.932 level in Panel c, and at the 0.176 level in Panel d. In the second-step of the demand estimation algorithm, the highest number of bidders within the subsample is used as the number of potential bidders (e.g., $n = 6$ is used if the relevant dataset includes only auctions with 5 or 6 bidders as in Panel a). Each dataset is subset across adjacent number of bidders to increase the number of observations, which can be seen in Appendix Figure D7b (auctions with more than 9 bidders are not included because they are too few).

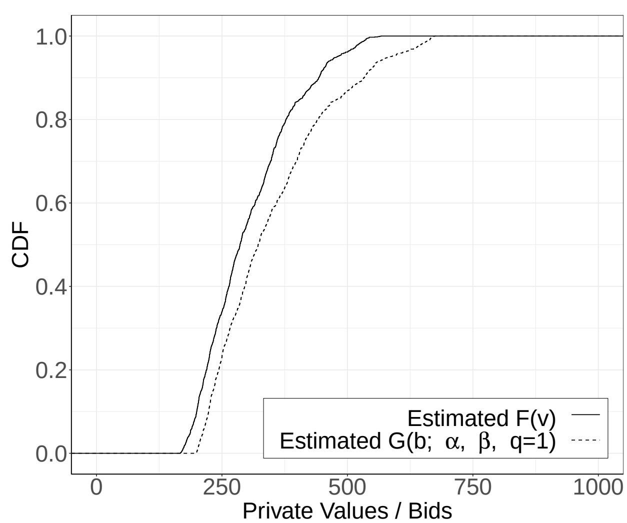
Figure D10: Additional results

(a) Over-identification test (b) Linearity of the logarithm of bids



Note: Panel a. Comparison of 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 produce indistinguishible densities. The KS-test does not reject the null hypothesis that the densities are equal at the standard levels. Panel b. 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 € . The linearity of the slope of the bid function with respect to q is tested by fitting a linear and a nonlinear model (second order polynomyal) 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 = 0.283).

Figure D11: Overbidding with respect to private values



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

E Profit-Maximizing Donation

This section presents additional results consistent with the results in the main text. All the estimates presented below report confidence intervals obtained through 401 bootstrap replications of the estimation algorithm with replacement.

E.1 Additional Covariates

Adding more covariates to those used in the main text does not change the optimal fraction donated substantially. The analysis in this subsection includes all the variables in Column 4 of Table 1 to the first-step regressions of both the demand and supply models. In practice, this means including variables categorized as "Additional Charity Dummies", "League/Match Dummies" and "Time Dummies" (see Appendix Section B1 for more details).

Table E1: Estimates with additional covariates

(a) Demand-side estimates

# of bidders		α	β
Quantile	n	[95% CI]	[95% CI]
99%	16	0.161	0.370
		[0.068, 0.260]	[0.122, 0.531]
95	14	0.159	0.370
		[0.068, 0.258]	[0.123, 0.531]
90	12	0.156	0.370
		[0.067, 0.254]	[0.123, 0.529]
75	10	0.153	0.369
		[0.066, 0.248]	[0.123, 0.529]
50	7	0.144	0.367
		[0.063, 0.234]	[0.123, 0.526]

(b) Supply-side estimates

Costs:	Quadratic	Cubic
π_0 (constant)	236.72***	239.77***
	(13.04)	(58.64)
π_1 (linear)	−427.80***	−465.13
	(58.22)	(677.48)
π_2 (quadratic)	210.87***	292.68
	(55.22)	(1,427.84)
π_3 (cubic)		−49.65
		(837.17)
Adj. R-squared	0.599	0.598
N	1,106	1,106

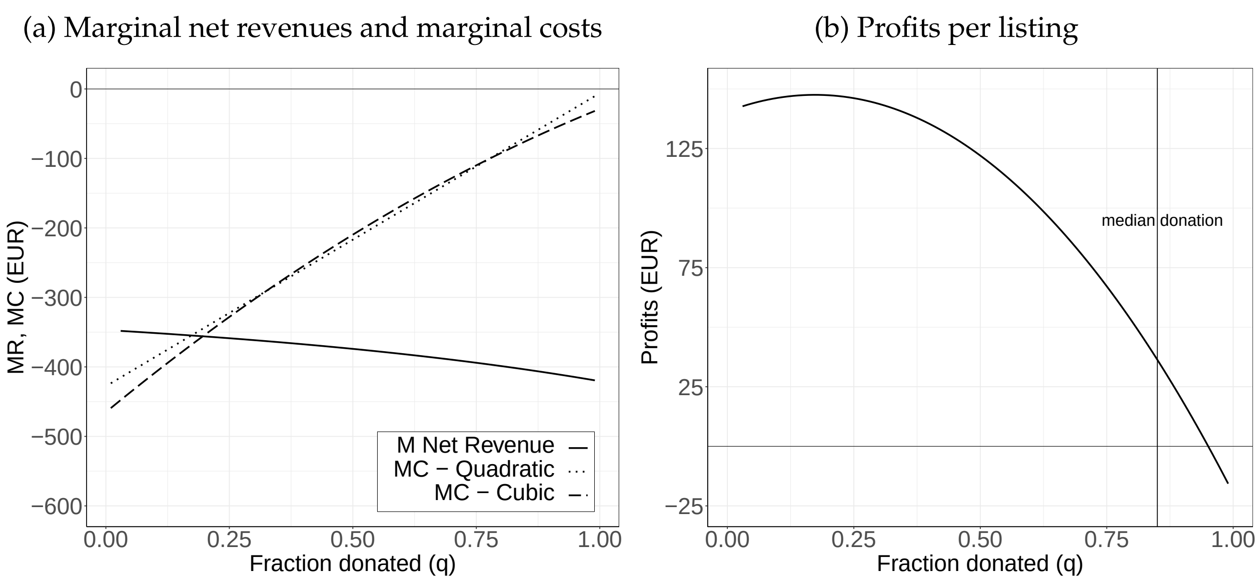
* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: Panel a. Demand-side estimates for the parameters α and β. 95% bootstrap confidence intervals (401 repetitions) in square brackets. Panel b. Supply-side estimates of the procurement costs parameters. Robust standard errors in parentheses. Both estimation routines follow the steps outlined in the main text with the only difference of adding the covariates discussed in the first paragraph of Appendix Section E.1 in the first-stage regressions.

The demand- and supply-side estimates are presented in Appendix Table E1. These new (α, β) estimates are similar both in magnitude and relative size to the main text estimates presented in Table 3, though slightly smaller and with larger confidence intervals. This may depend on the larger number of covariates, despite the same number of observations. Panel b reports the marginal cost estimates which are in line with the main text estimates in Table 5 (robust standard errors in parenthesis).

Appendix Figure E1 reports the resulting optimal fraction donated (Panel a) and the related profits (Panel b). Both plots are very similar compared to the analogous estimates in the main text (Figure 5) even though the optimal fractions donated are slightly smaller (0.17 for the quadratic case and 0.20 for the cubic case) than in Figure 5a ($\simeq$ 0.25). The 95% confidence interval for the quadratic cost case is $[0.11, 0.22]$ and for the cubic cost case is $[0.14, 0.24]$. Finally, Figure E2 shows that the welfare results are in line with those presented in the main text (Figure 7), though the highest welfare is slightly lower in this case. The optimal subsidy stays almost unchanged (Appendix Figure E2b).

Figure E1: Profit-maximizing donation with more covariates

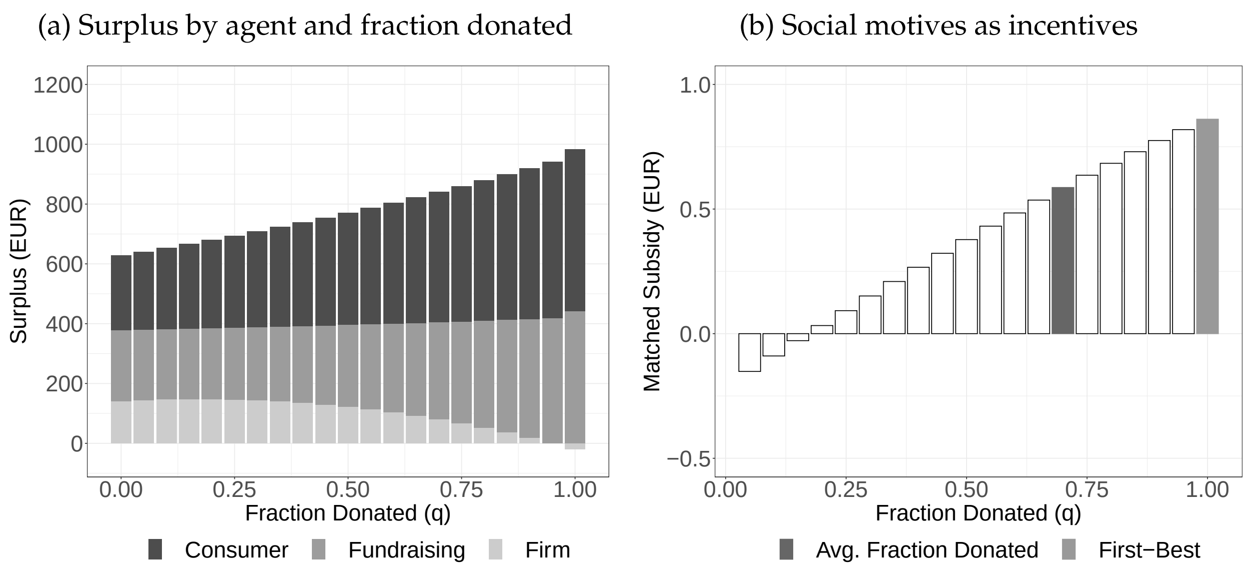


Note: Panel a. The optimal fraction donated is found at the intersection of marginal costs (dotted and dashed lines) and marginal net revenues (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) or cubic polynomials (dashed line). Panel b. The expected profits at different fractions donated. The vertical line at 0.85 indicates the median donation in the data. Both computations follow the steps outlined in the main text, while the estimation routine differs because it includes also the covariates discussed in the first paragraph of Appendix Section E.1 in the first-stage regressions.

E.2 Endogenous Reserve Price and Fraction Donated

The reserve prices and fractions donated are the result of bargaining between the provider of the item and Charitystars, creating potential endogeneity concerns. This section instruments reserve prices in the demand model and fractions donated in the supply model. On the demand side, a two-stage least square regression substitutes the OLS first-stage regression 3.6. The instruments for the reserve price are the average reserve price (in logs) and the average auction length (in logs) across auctions ending within 5 days of the focal listing's timestamp. Column 2 of Appendix Table C10 reports the coefficient estimates from this IV regression. The F-test is 22.589, and the over-identification test statistics (Sargan test) has a p-value of 0.784. The estimated α and β are reported in Appendix Table C11 and are 0.242 and 0.519 for $n = 16$, which are very close to the main text estimates in Table 5.

Figure E2: Welfare analysis with more covariates



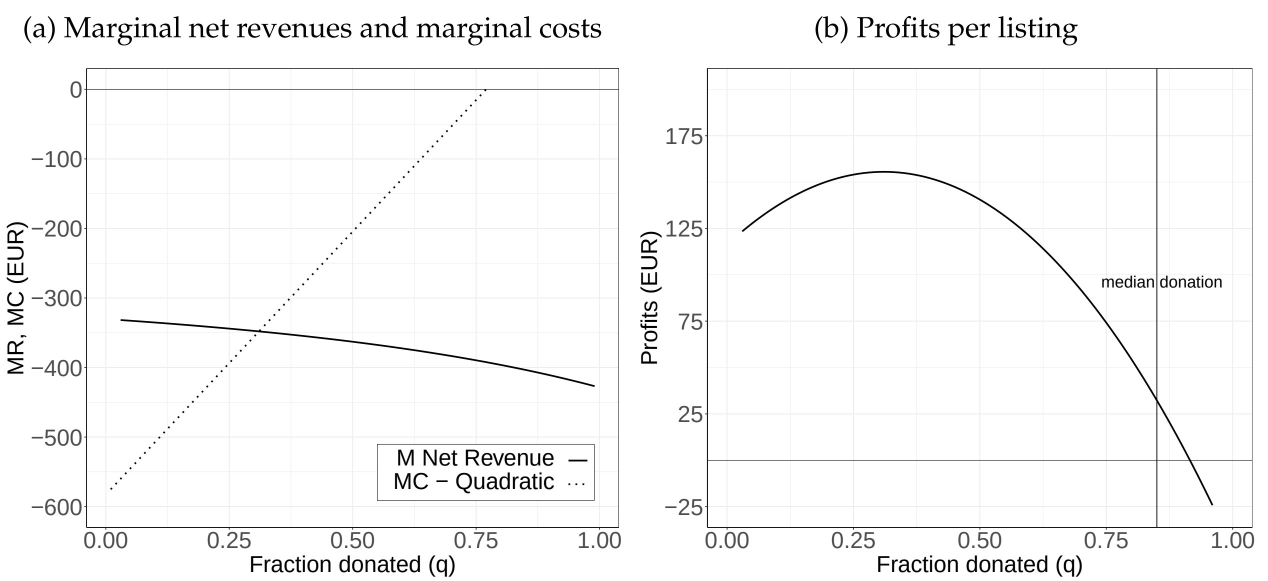
Note: Note: Panel a. The total welfare generated by different fractions donated. Panel b. The incentive compatible subsidy to the firm at different fractions donated. The dark and light gray bars represent the average observed fraction donated ($\simeq 0.7$) and the welfare-optimizing fraction donated (1.0), respectively. Both computations follow the steps outlined in the main text, while the estimation routine differs because it includes also the covariates discussed in the first paragraph of Appendix Section E.1 in the first-stage regressions.

On the supply side, instead of performing an OLS regression of the net reserve price on a polynomial expansion of q in the last step of the procedure described in Section 4, q and q^2 are instrumented with the average fraction donated (and its squared value) and the average player quality from the Fifa videogame (and its squared value) across concurrent auctions (also within 5 days). The estimated cost parameters are $\pi_0 = 252.08, SE : 40.63; \pi_1 = -582.69; SE : 250.35; \pi_2 = 378.20, SE : 243.77$. The F-test for the first endogenous regressor

(q) is 20.941 and for the second endogenous regressor (q^2) is 22.958. The over-identification test has a p-value of 0.903.

Despite the strong first stages for both the demand and supply models, the instruments would fail if the choice of the fraction donated and of the reserve price systematically responded to common shocks across concurrent auctions. To control for the popularity of the team and player, the covariates also include variables accounting for player and team quality (reflecting the player's real popularity), and variables like the number of listings of jerseys from the same team in the previous 3 weeks and the number of listings for the same player until the previous 2 weeks (reflecting the player's popularity on Charitystars.com). The controls also include charity characteristics and a charity counter which indicates the number of deals a charity stroke with the firm at any point in time. Thus, the instruments can effectively break the correlation between q and the reserve price, solving the endogeneity problem.

Figure E3: Profit-maximizing donation with instrumental variables

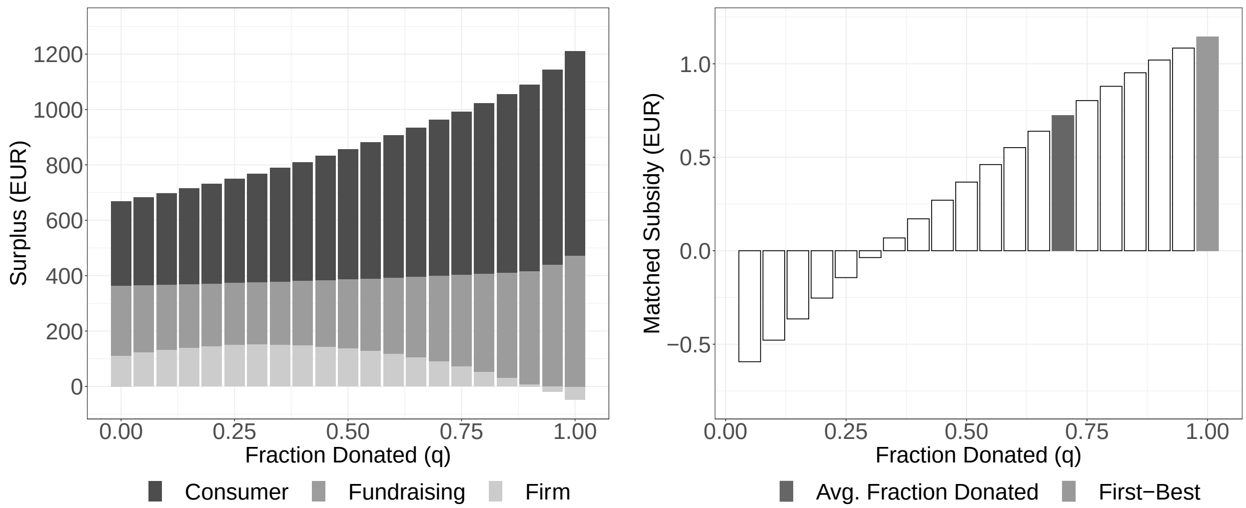


Note: Panel a. The optimal fraction donated is found at the intersection of marginal costs (dotted and dashed lines) and marginal net revenues (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) or cubic polynomials (dashed line). Panel b. The expected profits at different fractions donated. The vertical line at 0.85 indicates the median donation in the data. Both computations follow the steps outlined in the main text, while the estimation routine differs because it instruments the reserve price in the demand-side model and q in the supply-side model according to the discussion in Appendix Section E.2.

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 0.31 (95% C.I. [0.29,0.36]). Finally, Appendix Figure E4 finds that welfare changes are in line with those presented in the main text (Figure 7), though the slope of total welfare is steeper with IVs. As a result, the matched subsidy needed for a standard profit maximizing firm is about 0.7 (Appendix Figure E4b), which is slightly higher than 0.58 as shown in the main text.

Figure E4: Welfare analysis with instrumental variables

(a) Surplus by agent and fraction donated (b) Social motives as incentives



Note: Panel a. The total welfare generated by different fractions donated. Panel b. The incentive compatible subsidy to the firm at different fractions donated. The dark and light gray bars represent the average observed fraction donated ($\simeq 0.7$) and the welfare-optimizing fraction donated (1.0), respectively. Both computations follow the steps outlined in the main text, while the estimation routine differs because it instruments the reserve price in the demand-side model and q in the supply-side model according to the discussion in Appendix Section E.2.

E.3 Auction Heterogeneity

In the main text, bids, transaction prices and costs are first homogeneized and then transformed in euro by summing back the value of the heterogeneity of the median auction from the first-stage regressions in the demand- and supply-side models. This section replicates the same analysis considering the heterogeneity level at the 25^{th} and 75^{th} percentiles instead.

While the $\{\hat{\alpha}, \hat{\beta}, \hat{F}(\cdot)\}$ demand estimates are not affected because they are based on values in utils (i.e., auction heterogeneity only affects the computation of transaction prices in euro), the same is not true for the supply side marginal cost estimates. Appendix Table E2 displays the new marginal costs under the two heterogeneity levels for both the quadratic and cubic cases. Across columns, the coefficients show similar trends, and are also comparable with the main cost estimates in Table 5.

Appendix Figure E5a and Figure E5c plot the optimal fractions donated for the two heterogeneity levels respectively. The optimal donation for the 25^{th} quartile case is 0.16 (95%

C.I. [0.10, 0.23]) for the linear cost case and 0.21 (95% C.I. [0.18, 0.26]) for the quadratic cost case. The results are similar for the 75th percentile, where the optimal fraction donated is 0.23 (95% C.I. [0.17, 0.29]) for the linear cost case and 0.26 (95% C.I. [0.22, 0.30]). Appendix Figures E5b and E5d show the profitable deviations in each scenario. Finally, Appendix Figure E6 describes how the surplus to each party varies with the fraction donated for both heterogeneity level, as well as the required matched subsidy to incentivize a standard for-profit firm to behave like Charitystars. Despite the change in scale due to the different heterogeneity, the results are qualitatively similar to those discussed in Section 5.

Table E2: Estimates with different heterogeneity level

(a) 25th percentile

Costs:	Quadratic	Cubic
π_0 (constant term)	176.58***	183.59***
	(10.23)	(54.52)
π_1 (linear term)	−333.42***	−419.27
	(50.69)	(634.98)
π_2 (quadratic term)	175.49***	363.62
	(49.20)	(1,339.90)
π_3 (cubic term)		−114.18
		(786.24)
Adjusted R-squared	0.589	0.588
N	1,106	1,106

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

(b) 75th percentile

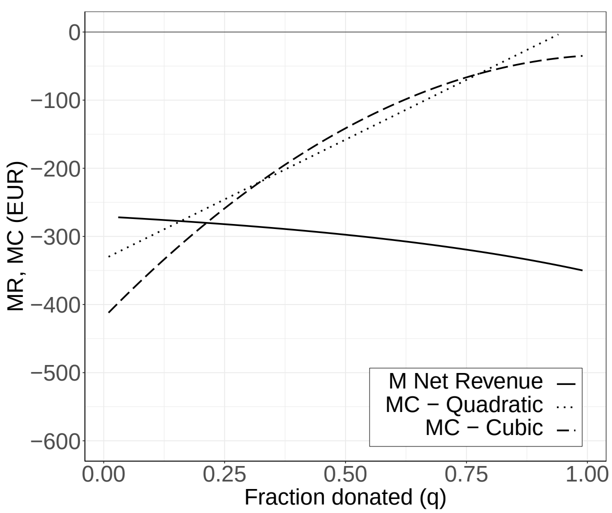
Costs:	Quadratic	Cubic
π_0	300.79***	312.75***
	(17.43)	(92.88)
π_1	−567.98***	−714.21
	(86.35)	(1,081.67)
π_2	298.94***	619.42
	(83.81)	(2,282.50)
π_3		−194.51
		(1,339.34)
Adj. R-sq.	0.589	0.588
N	1,106	1,106

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

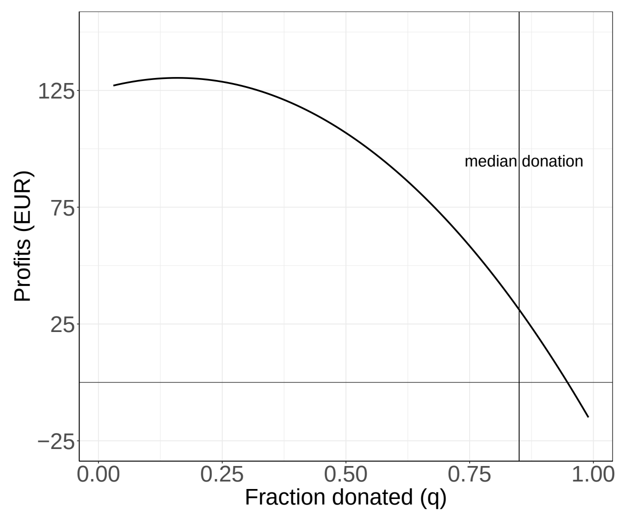
Note: Panel a. Supply-side estimates for the procurement cost parameters when the item characteristics are fixed at the 25th percentile of auction heterogeneity from the first-stage regression. Panel b. Supply-side estimates for the procurement cost parameters when the item characteristics are fixed at the 75th percentile of auction heterogeneity from the first-stage regression. Robust standard errors in parentheses.

Figure E5: Profit-maximizing donation with different heterogeneity levels

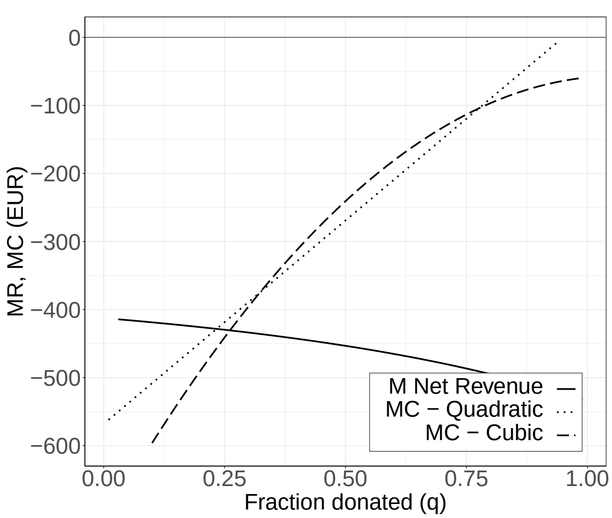
(a) Marginal net revenues and marginal costs
(25^{th} percentile)



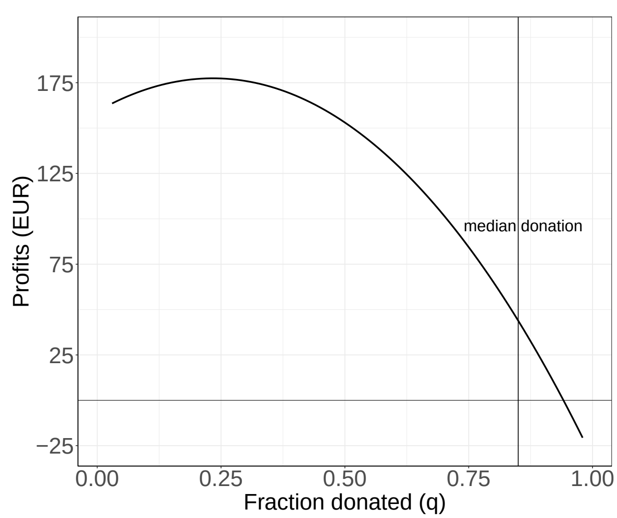
(b) Profits per listing
(25^{th} percentile)



(c) Marginal net revenues and marginal costs
(75^{th} percentile)



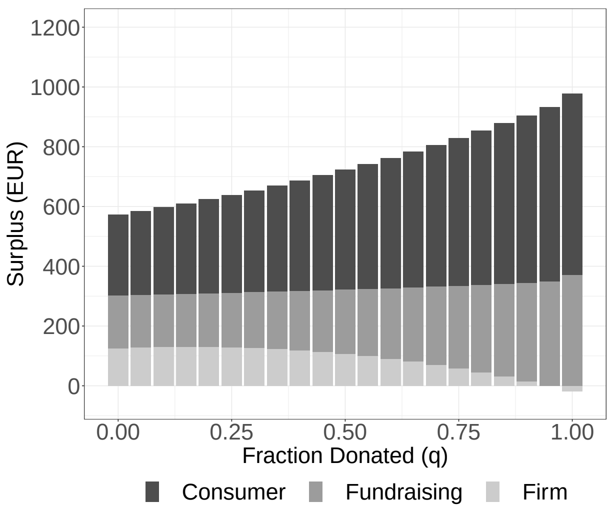
(d) Profits per listing
(75^{th} percentile)



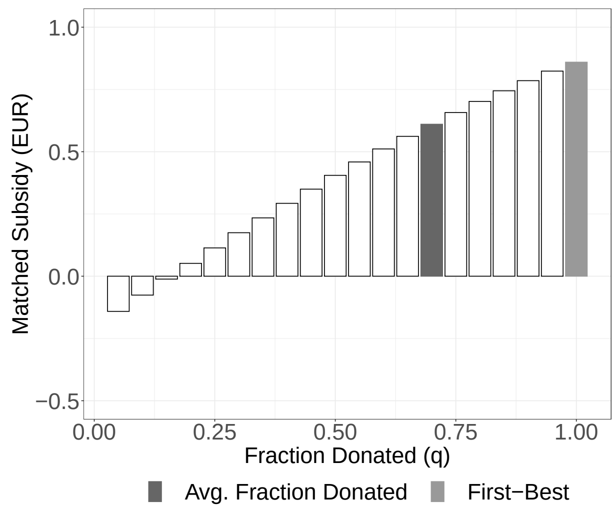
Note: Panels a and c. The optimal fraction donated is found at the intersection of marginal costs (dotted and dashed lines) and marginal net revenues (solid line). The marginal costs are estimated using quadratic polynomials (dotted line) or cubic polynomials (dashed line). Panel b and d. The expected profits at different fractions donated. The vertical line at 0.85 indicates the median donation in the data. All computations follow the steps outlined in the main text, with the difference that both demand- and supply-analyses consider the level of auction heterogeneity described in the subtitles.

Figure E6: Welfare analyses with different heterogeneity levels

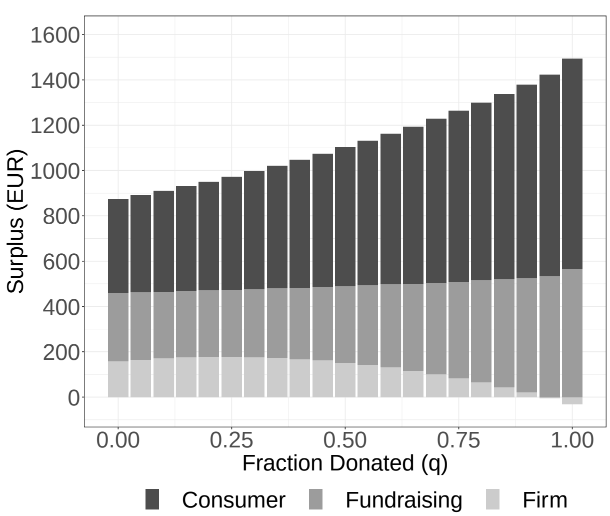
(a) Surplus by agent and fraction donated
(25th percentile)



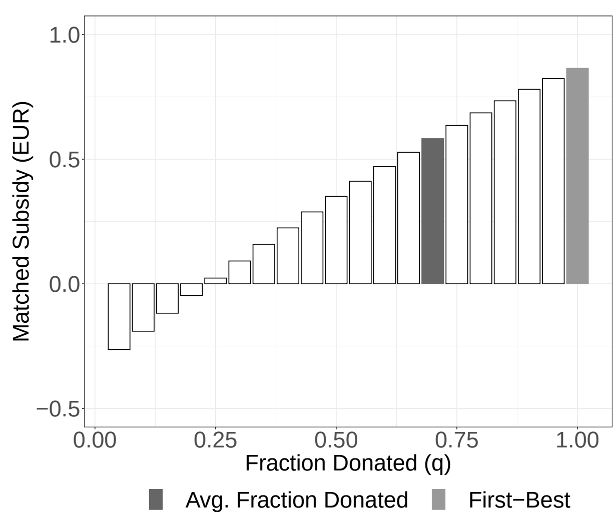
(b) Optimal subsidy
(25th percentile)



(c) Surplus by agent and fraction donated
(75th percentile)



(d) Optimal subsidy
(75th percentile)



Note: Panels a and c. The total welfare generated by different fractions donated. Panels b and d. The incentive compatible subsidy to the firm at different fractions donated. The dark and light gray bars represent the average observed fraction donated ($\simeq 0.7$) and the welfare-optimizing fraction donated (1.0), respectively. All computations follow the steps outlined in the main text, with the difference that both demand- and supply-analyses consider the level of auction heterogeneity described in the subtitles.

E.4 Provider Types

This section investigates whether the optimal fraction donated varies consistently based on the type of provider (available for 667 auctions). For some listings it is possible to observe whether the object is provided by either a football personality (e.g., a footballer, coach, or referee) and organization (e.g., a marketing firm working for footballers or a team) (315 auctions), or a charity (352 auctions).[15] Because players, coaches and teams are closely tied to their reference charities, this section re-estimates marginal costs either on the sample of auctions whose provider is known, or on the sample of auctions whose provider is a charity. Appendix Table E3 reports the marginal cost estimates for these two subsets. Because of the drop in the number of observations compared to Table 5, the analysis focuses only on the quadratic cost case. For the same reasons the confidence intervals estimated on the two subsets are slightly larger than that in the main text. Nevertheless, the estimates are consistent with those in Column 1 of Table 5.

Table E3: Cost estimation by provider type

Provider is:	(I) Charities and Soccer Players	(II) Charities Only
π_0 (constant term)	234.80***	262.28***
	(24.38)	(52.52)
π_1 (linear term)	−504.00***	−784.75*
	(107.52)	(460.80)
π_2 (quadratic term)	306.99***	601.48
	(96.96)	(473.99)
Adjusted R-squared	0.596	0.590
N	667	352

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

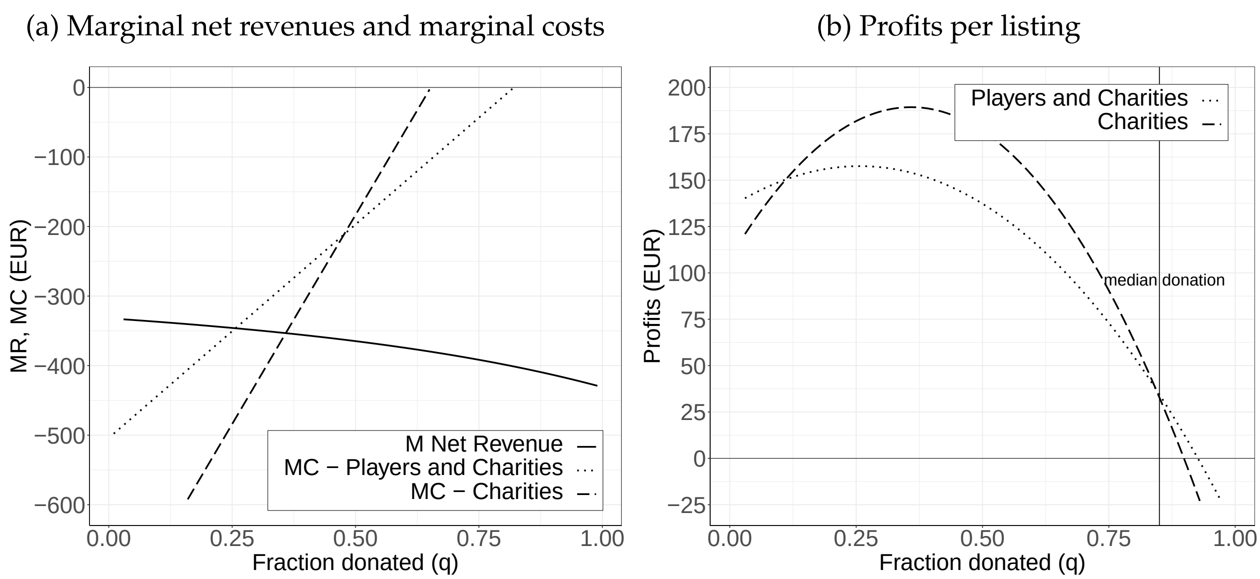
Note: Supply-side estimates of the procurement costs parameters. Each column estimates marginal costs on a different subset of the data according to the table header. Robust standard errors in parentheses.

Overall, the cost estimates indicate that footballers and charities have negative and upward sloping marginal costs. Figure E7 plots the optimal q obtained for both groups. The figure finds that marginal costs for the two groups intersect the marginal revenue curves approximately at the same value $q^* = 0.26$ (95% C.I. $[0.21, 0.30]$) for players and charities, and $q^* = 0.36$ (95% C.I. $[0.34, 0.38]$ for charities only, which is somewhat larger than the

[15]Performing this analysis for each charity is not feasible because only a few auctions per charity are observed and q is almost constant within each charity; this might depend on varying risk tastes across charities, with smaller charities favoring low donation percentages and high direct payments.

estimated $q^* \simeq 0.25$ in the full sample but still much lower compared to the observed data (see Figure 5a). Panel b of Appendix Figure E7 also shows a much larger profitable deviation compared to the main text.[16] In conclusion, the results are consistent with those reported in the main text despite the smaller dataset.

Figure E7: Profit-maximizing donation by provide type



Note: Panel a. The optimal fraction donated is found at the intersection of marginal costs (dotted and dashed lines) and marginal net revenues (solid line). Panel b. The expected profits at different fractions donated. The vertical line at 0.85 indicates the median donation in the data. Dotted lines refer to cost estimates considering both players and charities as providers while dashed lines refers to only charities. Both computations follow the steps outlined in the main text, while the estimation routine differs by provider type according to the discussion in Appendix Section E.4.

[16] Welfare analyses are not reported in this section because the focus is only on a subset of the data.

F Monte Carlo Simulations

The Monte Carlo simulations in this section (i) show that the estimation routine described in Section 3.4 returns consistent estimates for α and β, and (ii) provide empirical evidence supporting the claim that the estimates are not consistent when the fraction donated in the two auction types is very close (see Appendix A.4).

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 3.4. The true altruistic 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 from each auction.
3. Nonparametrically estimate the density of the winning bids (either through a triweight or a Gaussian kernel). The bandwidth is chosen using the rule-of-thumb. Trimming follows Guerre *et al.* (2000).[17]
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 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 ($q = .85$).
7. Match the quantile of the distribution of type B with those of the distribution of type A through Equation 3.5.
8. Find the couple (α, β) that minimizes the objective function in Equation 3.7 of the main text. The search algorithm constraints the parameters to be in the unit interval.

[17] For the Gaussian case the $h_{pdf} = 1.06\sigma n^{-1/5}$ and $h_{CDF} = 1.06\sigma n^{-1/3}$ where $\sigma = \min\{\text{s.d.}(w^k), \text{IQR}/1.349\}$, where 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 $h_{pdf} = h_{CDF} = 2.978\sigma n^{-1/5}$ (e.g., Härdle, 1991, Li *et al.*, 2002, Li and Racine, 2007, Lu and Perrigne, 2008).

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. To study the consistency of the estimates when there is only limited variation over q across auctions, Table F1 varies q across panels (instead of the kernel which is Gaussian in all panels). The results indicate that α and β are not consistently estimated 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 in the first two panel.

Moving to the consistency of the estimates, Tables F2 and F3 report different experiments, with the only difference that in the first table $F(\cdot) \sim [0,1]$, and $F(\cdot) \sim [-1,1]$ in the second table. Both tables show 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 0.04 of the true parameters.

Tables F2 and F3 are composed of 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. Empirically, the tables indicate that the root mean squared error (RMSE) decreases as the number of auctions grows (i.e., comparing RMSE across columns) at a rate that is close to $\sqrt{n}$ for all experiments. This finding suggests the asymptotic normality of the estimator.

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

T^A	T^B	μ_α	μ_β	Med_α	Med_β	$25\%_\alpha$	$75\%_\alpha$	$25\%_\beta$	$75\%_\beta$
				$q_A = 80\%, q_B = 85\%$					
500	500	0.0061	0.5330	0.0000	0.5342	0.0000	0.0000	0.5039	0.5579
1000	1000	0.0094	0.5348	0.0000	0.5298	0.0000	0.0034	0.5101	0.5546
				$q_A = 78\%, q_B = 85\%$					
500	500	0.0140	0.5400	0.0000	0.5367	0.0000	0.0148	0.5120	0.5602
1000	1000	0.0221	0.5465	0.0000	0.5364	0.0000	0.0290	0.5160	0.5620
				$q_A = 50\%, q_B = 85\%$					
500	500	0.2138	0.7186	0.1978	0.7052	0.1457	0.2743	0.6556	0.7778
1000	1000	0.2183	0.7220	0.2099	0.7144	0.1686	0.2653	0.6767	0.7636
				$q_A = 20\%, q_B = 85\%$					
500	500	0.2518	0.7512	0.2462	0.7460	0.2037	0.2948	0.7072	0.7878
1000	1000	0.2496	0.7492	0.2475	0.7459	0.2171	0.2837	0.7193	0.7791

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 dataset is generated according to $\alpha = 25\%$, $\beta = 75\%$ and $F(v)$ is assumed uniform in $[0,1]$. Each auction has 10 bidders. 401 repetitions.

Table F2: Monte Carlo simulation 1

T^A	T^B	μ_α	μ_β	Med_α	Med_β	$25\%_\alpha$	$75\%_\alpha$	$25\%_\beta$	$25\%_\beta$	$10\%_\alpha$	$90\%_\alpha$	$10\%_\beta$	$90\%_\beta$	$RMSE_\alpha$	$RMSE_\beta$
Gaussian kernel															
34	112	0.2793	0.7766	0.2789	0.7749	0.1589	0.4068	0.6674	0.8944	0.0823	0.498	0.5912	0.99	0.1543	0.1423
172	560	0.2601	0.7583	0.2555	0.7558	0.1999	0.3115	0.701	0.8058	0.168	0.3671	0.6715	0.8621	0.0786	0.0724
100	100	0.2593	0.7579	0.2539	0.7509	0.1696	0.3431	0.6761	0.8352	0.1168	0.4252	0.623	0.9049	0.1164	0.1067
500	500	0.2553	0.7541	0.251	0.75	0.2113	0.2935	0.7148	0.7868	0.1778	0.3365	0.6826	0.8284	0.0619	0.0565
1000	1000	0.2527	0.7518	0.2499	0.7499	0.2236	0.2825	0.7249	0.7787	0.2	0.3047	0.704	0.7995	0.0412	0.0375
Triweigth kernel															
34	112	0.2044	0.7131	0.1766	0.6898	0.0996	0.3039	0.6193	0.8028	0.0456	0.3848	0.5654	0.8887	0.1403	0.1299
172	560	0.2158	0.7208	0.212	0.7166	0.1625	0.261	0.6697	0.763	0.1303	0.3075	0.6401	0.8075	0.0784	0.0718
100	100	0.2005	0.7092	0.1971	0.7062	0.1279	0.2636	0.6419	0.7653	0.0764	0.3241	0.5971	0.8238	0.1085	0.099
500	500	0.2209	0.7254	0.2169	0.7193	0.1854	0.2567	0.6926	0.7596	0.1485	0.2967	0.6587	0.7956	0.0621	0.0562
1000	1000	0.2293	0.7323	0.2286	0.7313	0.2015	0.257	0.7067	0.756	0.1833	0.2783	0.6898	0.7778	0.0437	0.0394

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 triweight kernel (bottom panel). The dataset 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_α	Med_β	$25\%_\alpha$	$75\%_\alpha$	$25\%_\beta$	$25\%_\beta$	$10\%_\alpha$	$90\%_\alpha$	$10\%_\beta$	$90\%_\beta$	$RMSE_\alpha$	$RMSE_\beta$
Gaussian kernel															
34	112	0.2813	0.7739	0.2705	0.7723	0.1659	0.3989	0.681	0.8677	0.0926	0.4988	0.6131	0.977	0.152	0.129
172	560	0.2588	0.755	0.2553	0.7475	0.202	0.3058	0.7104	0.7971	0.1712	0.3608	0.6775	0.8382	0.0725	0.062
500	500	0.2552	0.7521	0.2517	0.7497	0.2153	0.2894	0.7196	0.7827	0.184	0.3298	0.6946	0.8128	0.0571	0.0474
1000	1000	0.253	0.7506	0.251	0.7489	0.2259	0.2806	0.728	0.7747	0.2061	0.301	0.7096	0.7915	0.0375	0.0314
Triweigth kernel															
34	112	0.2172	0.7327	0.1933	0.7248	0.1141	0.3087	0.6448	0.8089	0.0595	0.4053	0.5893	0.9087	0.1362	0.1187
172	560	0.223	0.7316	0.2208	0.7281	0.1696	0.2663	0.6855	0.7705	0.1382	0.309	0.656	0.8127	0.0721	0.0612
500	500	0.2284	0.7354	0.2228	0.7328	0.1943	0.2636	0.7055	0.7641	0.1595	0.3005	0.6782	0.7947	0.057	0.0469
1000	1000	0.2346	0.7392	0.2323	0.7372	0.2091	0.2595	0.7182	0.7591	0.1913	0.2811	0.7012	0.78	0.0391	0.0323

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 triweight kernel (bottom panel). The dataset 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.

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