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ABSTRACT

For companies, it is essential to obtain information about customers' preferences to successfully market their products and services. Experimental auctions are a promising method for acquiring such information considering that they are incentive compatible and non-hypothetical. Their applicability to solving real-world problems has been limited by the need to conduct these with a representative sample. While most research on experimental auctions relies on laboratory experiments with students as participants, more recently, experimental auctions in the field have become increasingly important. In this paper, we explore a novel way of conducting experimental auctions in the field using online communities of potential consumers. We discuss design challenges and present marketing applications.

KEYWORDS: Experimental auctions; Field experiments; Market research; Value elicitation

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1. Introduction

In the past few decades, online auctions have become an integral part of B2B, B2C, and C2C transactions. The eBay platform alone currently hosts over 130M users offering almost 2B listings for an annual gross merchandise volume of around $80B.[1] This development has not gone unnoticed by marketing, management, and economics scholars, who have been using online auction platforms as rich data sources for their research virtually since the advent of online auctions.[2] We contribute to the literature on online auctions by providing a methodological evaluation of using online experimental auctions for demand elicitation, i.e., online auctions being used as 'experimental auctions', i.e., auctions in which bids are elicited from participants to measure their maximum willingness-to-pay (WTP) for novel or modified products as well as the changes in WTP for such products compared to existing ones (e.g., organic food products compared to non-organic food products).[3] Such information about potential customers' preferences is essential for businesses to successfully market their products and services.

Offline experimental auctions have been used widely to obtain information about potential customers' preferences since Hoffman *et al.*'s (1993) seminal contribution.[4] A major advantage of experimental auctions is that they incentivize participants to "put their money where their mouths are," in contrast to traditional methods that measure preferences in a hypothetical setting, such as focus groups, surveys, market tests, laboratory pre-test markets, and conjoint analysis, in which consumers tend to overstate their WTP.[5] Experimental auctions are also more informative than observing purchase behavior in the field, such as those provided by scanner data. Consumers' in-store purchases only reveal whether a

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[1] https://investors.ebayinc.com/fast-facts/default.aspx (accessed on October 20, 2023).
[2] A wide variety of exciting questions have been addressed using data collected from online-auction platforms, including strategic bidding in auctions (Lucking-Reiley, 1999; Barrot *et al.*, 2010; Zeithammer and Adams, 2010; Malmendier and Lee, 2011), the impact of customer community participation on customer behaviors (Algesheimer *et al.*, 2010), the effect of a fraction of the proceeds being donated to charity on selling prices (Popkowski Leszczyc and Rothkopf, 2010), the impact of the quality of a seller's offline retail location on the seller's auction outcomes (Kuruzovich and Etzion, 2018), and the impact of the "Made in USA" claim on consumer demand (Kong and Rao, 2021).
[3] The study of online experimental auctions was pioneered by Barrot *et al.* (2010) and Zeithammer and Adams, (2010).
[4] See Lusk and Shogren (2007) for an overview of the literature. They report that more than a hundred academic studies that used experimental auctions for preference elicitation.
[5] See, e.g., Shogren *et al.* (1999), List and Gallet (2001), List (2001), and Jacquemet *et al.* (2009). Ding (2007) and Park et al. (2008) propose ways to complement conjoint analysis with incentivizes inducing participants to reveal their true preferences.

consumer's WTP exceeds the price (Shogren *et al.*, 1999). In contrast, experimental auctions can reveal at the individual level whether a product will be purchased at every possible price point.

While most research on experimental auctions relies on laboratory experiments,[6] more recently, experimental auctions in the field have become increasingly important. In contrast to laboratory experiments, field experiments can reach the target audience in their typical purchasing context and they are less expensive in that the participants generally do not need to be compensated monetarily for their participation (Lusk and Fox, 2003; Lusk, 2010). Relatedly, relatively expensive products can only be evaluated in the field because the compensatory fees in a laboratory environment are not only prohibitively costly but they may also bias WTP measurement (Rutström, 1998).[7] In this paper, we explore a novel way of conducting experimental auctions in the field using online communities.[8] In particular, we discuss some design challenges and present applications using data collected with an online platform tailored for experimental auctions.

Online experimental auctions potentially combine the best of laboratory and offline field experimental auctions for several reasons.[9] First, it is relatively easy to attract a representative sample of the relevant pool representative of potential customers in an online experimental environment. In contrast, field experiments in retail shops only attract the visitors to the shop so that no information is obtained from consumers who do not visit the shop. Similarly, it is logistically difficult, if not prohibitively costly, to get a representative sample of the entire population in a physical laboratory. Moreover, typical lab participants may differ significantly from the general population in terms of preferences (Snowberg and Yariv, 2021).

[6] See Canavari *et al.* (2019) for a recent review.
[7] Another disadvantage of lab experiments is that the participant pool mainly consists of undergraduate students. However, this is not a limitation of the lab in and of itself in that the researcher could invite a non-standard participant pool in the lab. See, e.g., Noussair *et al.* (2004) for such an 'artefactual field experiment' (Harrison and List, 2004) in the context of experimental auctions.
[8] Lusk (2010) advocates the use of online experimental auctions. Chen and Konstan (2015) discuss design choices for online field experiments in economics and computer science.
[9] Early papers on offline field experimental auctions include List and Shogren (1998), Shogren *et al.* (1999), List (2001), Lusk *et al.* (2001), and Lusk and Fox (2003).

Second, recruitment for an online experimental auction is considerably cheaper and faster than for a laboratory or an offline field experiment (Chen and Konstan, 2015). Similar to online surveys, participants can be recruited from existing pools of participants for an online experimental auction while in offline field experiments, researchers may have to spend considerable time and resources to recruit participants and organize experimental sessions. Furthermore, participants in online experimental auctions require little to no monetary compensation because they pay with their own money if they win an auction. As a consequence, online field experiments can afford and facilitate sample sizes several orders of magnitude greater than in a typical laboratory or offline field experiment. Thus, online experimental auctions have the logistical advantages of online surveys but without losing the realism of a laboratory or field experiment.

Third, in an online experimental auction researchers have more control over the interaction between themselves and the participants because all communication is through the participants' devices. Even in a tightly controlled laboratory environment, there is some personal interaction between the researcher and the participant, if only to show the participant to her computer terminal or to settle the transaction of the auctioned products. Such interaction may give rise to an experimenter demand effect in that participants may adapt their behavior because they feel being 'watched' (Zizzo, 2010).

A fourth potential advantage of online experimental auctions is that participants can relatively easily obtain information about close substitutes to the auctioned product and, because the auction is real, there is an inherent incentive to do so. This adds to the realism of the experiment in that in practice, consumers can also acquire such information to determine whether to purchase a product. Of course, the increase in realism should be traded off against the loss of control over such information acquisition.

Researchers running experimental auctions on existing online auction platforms face a number of challenges. First, the researchers should control the supply side of the market so that they can focus purely on demand. Moreover, the auction mechanism used should yield unbiased demand estimates, which is difficult if a current high bid discourages low-value bidders to participate. Additionally, the online platform requires broader recruitment than those people who self-select into marketplaces like eBay.

In the remainder of this paper, we will discuss in detail how these challenges can be dealt with. We do so by discussing the auction mechanism, potential experimental designs, and the experimental procedures in Section 2. In this section, we also highlight how data from online experimental auctions can be analyzed. Section 3 includes four case studies which showcase how online experimental auctions can be used for marketing research related to communicating scarcity of supply, providing after-purchase discounts, consumer attitudes towards brands, and innovation. Section 4 contains a conclusion.

2. How to Run Online Experimental Auctions

This section describes how to run online experimental auctions; this description complements existing literature providing guidance on running experimental auctions in other contexts such as that in Lusk and Shogren (2007), Alfnes and Rickertsen (2011), and Canavari et al. (2019), and in the cause of multi-unit auctions, Khezr and Cumpston (2021). We spell out the rules of the auction mechanism and compare it to other WTP elicitation mechanisms in section 2.1. We discuss potential experimental designs and procedures in section 2.2, and data analysis in section 2.3.

2.1 Auction mechanism

The auction mechanism used in online experimental auctions is the multi-unit Vickrey auction introduced by Vickrey (1961). In this auction, $n \geq 1$ units of an item are offered for sale. Bidders independently submit a single bid. The n highest bidders obtain one unit of the item and pay a price equal to the $(n+1)$th highest bid. In the case of a tie, a random draw determines the winner. To ensure that bidders have an incentive to reveal their true value, winners pay the highest losing bid. More precisely, under the assumption of private values, the multi-unit Vickrey auction is 'incentive compatible': it has a unique equilibrium in weakly dominant strategies in which all bidders submit a bid equal to their value for the item. This result holds true regardless of the bidders' beliefs about the values for competing bidders and bidders' risk attitudes.[10] As a result, the multi-unit Vickrey auction elicits bidders' WTP. Notice that this auction mechanism generalizes the well-known second-price sealed-bid auction in that it allocates multiple items under the restriction that bidders can obtain at most a single unit of the item. Vickrey (1961) describes this implementation of the Vickrey auction as "first-rejected-bid pricing," which, according to him, has the advantage of "reducing effort and expense devoted to socially superfluous investigation of the general market situation" (p. 26).

The multi-unit Vickrey auctions have several advantages over other incentive-compatible mechanisms such as the English auction, the eBay auction, the Becker-DeGroot-Marschak mechanism (BDM), the random *n*th price auction, and the second-price sealed-bid auction. In the English auction, the price of the auctioned item is gradually raised. Bidders can indicate at each price whether they are willing to buy the item for that price. The item is sold when the auctioneer reaches a price at which n bidders remain. These bidders win an item and pay the final announced price. It is well known that it is a weakly dominant strategy for bidders to step out when the price reaches their value. In fact, Li (2017) shows that the English auction is "obviously strategy proof" in contrast to the multi-unit Vickrey auction. This is in line with lab evidence showing that bidders are more likely to bid their value in the English auction than in the Vickrey auction (Kagel *et al.*, 1987; Li, 2017; Breitmoser and Schweighofer-Kodritsch, 2022). However, the English auction is ill-suited to measure WTP in large-scale field experiments for several reasons: (1) the English auction is time consuming, (2) all bidders have to be present at the same time to submit their bids, and (3) the auction does not reveal the WTP of the highest n bidders because the auction stops as soon as price reaches the $(n+1)$th value.

The eBay auction is tailored to take care of these downsides of the English auction. The eBay auction has the same rules as the English auction with the exception that bidders can submit 'proxy bids'. A proxy bid can be submitted at any time during the auction and should exceed the current highest bid. The bidder's bid is automatically raised when another bidder raises the price, up to a price equal to the

[10] Truthful bidding ceases to be a weakly dominant strategy if the auctioned good exhibits a common value element (Milgrom and Weber, 1982) and in the case of allocation dependent externalities (Jehiel *et al.*, 1996) or financial externalities (Goeree *et al.*, 2005; Maasland and Onderstal, 2007). Typical consumer commodities arguably do not have such characteristics.

bidder's proxy bid. The eBay auction can be seen as a hybrid between the English auction and the multi-unit Vickrey auction in that if all bidders only submitted proxy bids, the n highest bidders win an item and all pay the $(n+1)$th highest bid. Barrot *et al.* (2010) observe bidders behaving strategically in both English and eBay auctions leading to more distorted WTP measuring than the Vickrey auction. Relatedly, Zeithammer and Adams (2010) document patterns in eBay bidding data inconsistent with bidders bidding their true value.

The BDM (Becker *et al.*, 1964) elicits WTP using the following mechanism. A number is drawn randomly from a particular price range. A potential buyer is informed about the price range and is asked to submit a bid within this range. If the buyer's bid is higher than the number drawn, the buyer obtains the item and pays a price equal to the number drawn. Otherwise, the buyer does not obtain the item. An advantage of using the BDM mechanism is that participants receive immediate feedback, which would allow in-store applications of the mechanism. There are a number of disadvantages. One is that the experimenter risks selling items for a very low price. More importantly, laboratory evidence suggests that the BDM biases the values elicited in the sense that the bounds of the interval from which the price is drawn have an impact on the bids submitted (Bohm *et al.*, 1997). More in general, the BDM performs worse than the Vickrey auction in terms of biases, bid dispersion, and convergence to truthful revelation (Noussair *et al.*, 2004).

In the random nth price auction (Shogren *et al.*, 2001), bidders independently submit bids. One of the bidders is selected at random. All bidders who submitted a strictly higher bid than this bidder obtain an item and pay the bid submitted by this bidder. Shogren *et al.* (2001) argue that in the random nth price auction, off-margin bidders, i.e., bidders whose values are likely to be much lower or much higher than the market-clearing price, have greater incentives to reveal their value than the multi-unit Vickrey auction. They find support for this in the lab. At the same time, they also observe that the Vickrey auction works better for bidders whose values are likely to be close to the market-clearing price. In addition, the random *n*th price auction is financially very risky for the auctioneer if the sample size is large.[11]

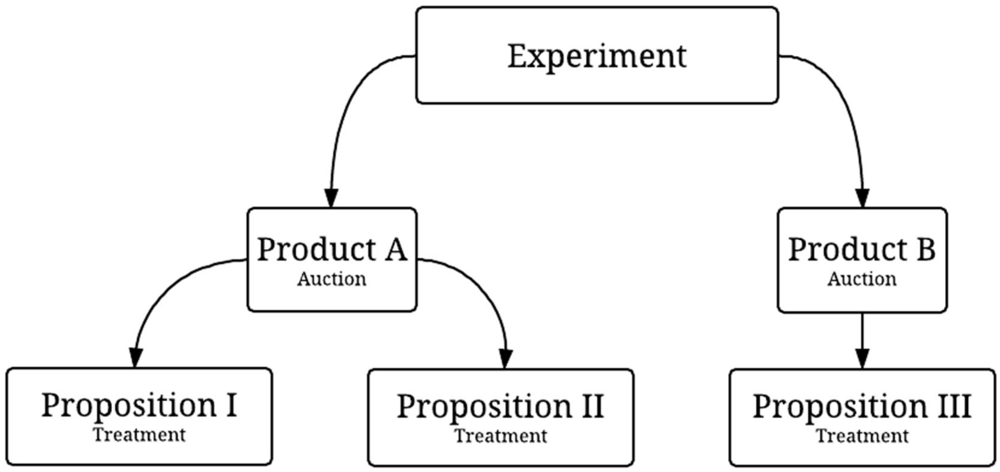
The second-price sealed-bid auction uses the same rules as the multi-unit Vickrey auction with the difference that only one item is sold (i.e., $n = 1$). Allowing for multiple winners might be desirable from a methodological point of view though. First, the mere possibility of a large number of winners provides an incentive to bidders who are convinced that they will not place the highest bid, to still place a bid that reflects their WTP (Lusk *et al.*, 2007). Second, to safeguard the platform's reputation, the number of winners can be increased to ensure that the auction price is "not too high". Both winners and losers might be suspicious about the platform submitting fake bids to drive up the price winners pay or to prevent bidders from winning at too low a price.

2.2 Experimental designs and procedures

Online auction platforms can make use of field experiments to test hypotheses of interest. The platform on which the experiments reported in Section 3 were run, makes use of framed field experiments (Harrison and List, 2004) in the sense that participants are to some extent aware that they participate in an experiment: they know that the online platform is used for research purposes (although they probably do not know that they may be randomly assigned over treatments). A typical experimental design is of the $k \times m$ type where k is the number of different products auctioned and m represents the number of ways the auctioned products are presented to the bidders. Figure 1 shows that other experimental designs are possible too. The objects auctioned may only vary marginally, e.g., in the color of the product. Usually, the objects are single products but it is also possible to run experiments with bundles of products. The researcher may also be interested in the effect of the way the products are presented on WTP. For example, what is the effect of disclosing particular information about a product? Or what is the best way to visually present the product to the buyers? Consecutive experiments may be run to allow for repeated measurements of WTP.

[11] To reduce this risk, while retaining the incentives to reveal value across the board, the experimenter may use a pre-determined price above marginal costs that is not communicated to the bidders (Lusk *et al.*, 2001).

Figure 1 An example of an experimental design



Notes. In this experimental design, there are two different products, A and B. Product A has two treatments while product B only has one.

To foster internal and external validity, an online auctions platform should (1) recruit from a pool representative of the potential customers and distributes participants in a balanced way over the experimental treatments, (2) get a representative sample of the participant pool to participate in the auction, (3) incentivize participants to bid truthfully, and (4) establish itself as a reputable party for delivering products as promised, collecting payments, etc. The following experimental procedures are aimed at reaching those targets. First of all, members of a representative participant pool are invited to bid in an auction. Participants can enter the auction only once. To ensure balance across treatments, participants are randomly allocated over the treatments. To mitigate selection effects, the invitation does not specify the product that is up for sale. The invitation also contains information about when the auction closes and how participants are expected to determine their bids. To induce participants to bid truthfully, the researcher explicitly requests them to bid their WTP.[12] Participants are also instructed to

[12] Masuda *et al*. (2022) find in a laboratory study that informing participants that multi-unit Vickrey auctions are incentive compatible substantially increases the likelihood that the participants bid their value.

bid zero if they are not prepared to pay anything for the object. The researcher does not provide experimenters with a budget. Instead, winners pay for the item from their own money.[13]

The online auction platform arranges for the participants' informed consent before they enter the experiment so that they are aware of their rights and obligations. After providing informed consent, the platform gives participants information about the item being auctioned along with the rules of the auction. To obtain additional information about the participation, the platform can ask participants to fill out a survey. To establish and retain a good reputation, the platform informs participants after the auction about the results which may include the top bid, the price paid by the winners, and about participants' own position in the bid distribution (*e.g.*, "50% of the participants placed a bid higher than yours.").

2.3 Data analysis

In this section, we discuss the data analysis.[14] Differences in average WTP across treatments can be straightforwardly compared on the basis of t-tests. Mann-Whitney/Kolmogorov-Smirnov tests can be used to compare the WTP distributions between treatments.

The data can also be used to estimate optimal pricing strategies. Suppose the researcher runs T treatments, labeled $t = 1, \dots, T$. Suppose the elicited WTPs $w_t^{(1)}, w_t^{(2)}, \dots, w_t^{(N_t)}$ of the N_t participants in treatment t are ordered in such a way that

$$w_t^{(1)} \geq w_t^{(2)} \geq \cdots \geq w_t^{(N_t)}.$$

Using these observations, the inverse demand curve among the participants in treatment t can be readily estimated:

$$\hat{P}_t(Q) = w_t^{(Q)}, Q = 1,2, \dots, N_t.$$

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[13] Experimental evidence strongly suggests that the Vickrey auction is better able to elicit bidders' WTP if they are required to pay with earned money rather than with windfall money (Jacquemet *et al.*, 2009).
[14] This section builds on Lusk (2010) and Lusk and Shogren (2007).

The corresponding estimated demand curve is given by:

$$\widehat{D}_t(p) = max_Q \left\{ Q | w_t^{(Q)} \geq p \right\}.$$

The profit-maximizing price for treatment t can be estimated as follows using a grid search over the actual bids obtained:

$$\hat{p}_t^* \in \underset{p \in \left\{ w_t^{(1)}, \ldots, w_t^{(N_t)} \right\}}{\operatorname{argmax}} \widehat{D}_t(p)(p - c),$$

where c denotes the unit production costs. The implied optimal profits are

$$\hat{\pi}_t^* = \widehat{D}_t(\hat{p}_t^*)(\hat{p}_t^* - c).$$

Comparing the profitability across treatments is not straightforward in a statistical sense: Each treatment produces only one observation for the estimated optimal profits. The following two techniques can be used to test whether treatments differ significantly in terms of expected profits. The first is recombinant estimation (Mullin and Reiley, 2006). The method draws subsamples of size $S \ll N_t$ from the observations in treatment t for all treatments and calculates the implied optimal profit from each draw. By doing so, the researcher obtains many observations that can be compared statistically using software developed by Mullin and Reiley (2006). Alternatively, the researcher compares optimal profits across treatments taking a demand curve $D_\alpha(p)$ as a starting point, where D_α has a specific functional form that depends on a vector α of parameters. Let $\pi(\alpha)$ denote the corresponding optimal profits. After estimating the parameter vectors α_t and α_s for treatments t and s respectively, the null hypothesis $\pi(\alpha_t) = \pi(\alpha_s)$ can be tested, for instance on the basis of a Wald test.

Optimal profits across treatments can be readily compared statistically if consumers' WTPs are drawn i.i.d. from an exponential distribution. Suppose that the cumulative distribution function from which each consumer i's WTP in treatment t, w_{it}, is drawn is given by

$$F_t(w) = 1 - e^{-\frac{w}{\lambda_t}}, w \geq 0, \lambda_t > 0.$$

The profit-maximizing price p^* follows from

$$p^* \in \underset{p}{\operatorname{argmax}}\, N \times P\{w_{it} \geq p\}(p - c)$$

$$= \underset{p}{\operatorname{argmax}}\big(1 - F_t(p)\big)(p - c)$$

$$= \underset{p}{\operatorname{argmax}}\, e^{-p/\lambda_t}(p - c),$$

where N is the total number of potential consumers. The first-order condition of the maximization problem is:

$$e^{-p^*/\lambda_t} - \frac{e^{-p^*/\lambda_t}(p - c)}{\lambda_t} = 0 \Leftrightarrow p^* = c + \lambda_t.$$

As a result, the profit-maximizing price is equal to the marginal costs plus a mark-up equal to the distribution function's rate parameter. Under the assumption of exponentially distributed WTP, treatments can be compared in a statistically meaningful way by comparing the estimated optimal mark-ups. In the case study presented in section 3.4, we will do so in a setting where the WTP distribution curves approximate the exponential distribution.

3. Case Studies

In this section, we present four studies that were carried out using the online experimental auction platform Veylinx, which has been designed for the purpose of market research.[15] Hundreds of online field experiments have been conducted on the platform, mostly for Fortune 500 companies, to measure WTP for products and services ranging from food to consumer electronics and mobile subscriptions. Appendix A contains screenshots and translations of the instructions for all treatments of each experiment.

[15] https://veylinx.com.

3.1 Scarcity and effort signaling

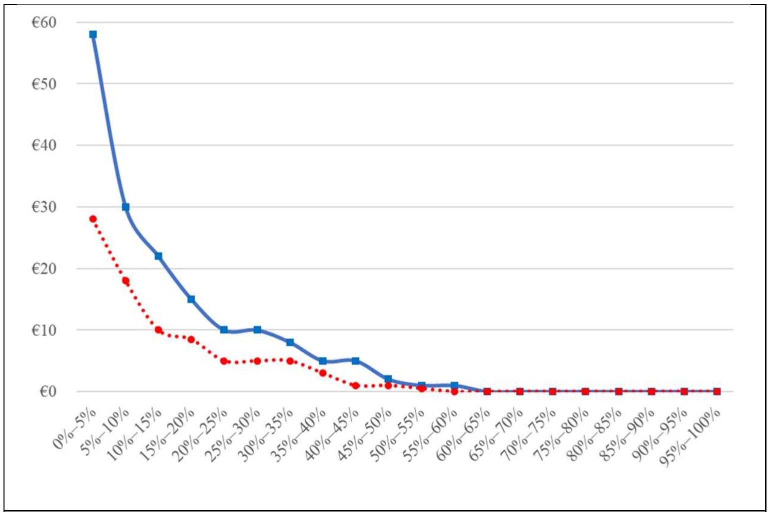
Communicating scarcity of supply is a common marketing tactic to increase the perceived value of a product, which in turn can increase its sales (see Cialdini, 2008, for a popular-science discussion of this marketing tactic). Another method to increase perceived value is operational transparency. Operational transparency consists of providing information about *how* a product is produced. Studies show that emphasizing producer's effort can increase consumers' hypothetical WTP (Buell and Norton, 2011; Morales, 2005).

An online experimental auction was conducted to test whether supply scarcity and operational transparency affect consumers' WTP in the field. The focal object is a traffic bollard from Amsterdam and are aptly named *Amsterdammertje* (*Eng.* the small one from Amsterdam). These bollards are commonly found in the narrow streets in the city center of Amsterdam and are considered iconic. The municipality of Amsterdam has a policy of actively removing and selling these bollards. Many people buy the bollards to put them on display in their backyard for instance to show allegiance to the city of Amsterdam.

The experiment consists of a 2 (Scarcity signal absent, Scarcity signal present) x 2 (Operational transparency absent, Operational transparency present) between-subject factorial design. The baseline treatment consists of an advertisement with a picture of a typical *Amsterdammertje* and specifications about its size and weight (see Appendix A). The scarcity signal consists of the following message: "All *Amsterdammertjes* will be removed from the street scene. Grab your chance to buy one before it's too late." Operational transparency consists of a message stating: "It took a bit of effort but we managed to get it out of the ground… (With permission from the municipality.)" We invited 3,745 consumers to participate in the experimental auction, 1,091 responded to the invitation and 870 participants completed the flow, which constitutes the final sample used for analysis.

Figure 2 provides an aggregated view of the demand curve. 40.3% of the participants placed zero as a bid. The mean bid is €7.45 while the average bid in the top 20% percentile is €27.60 (Table 1). Combined, these statistics imply that the distribution of bids is not normally distributed.

Figure 2 Scarcity and effort signaling: Demand curves



Notes. The demand curve with round/square data points represents the baseline treatment (n = 235)/ the scarcity treatment (n = 218).

Table 1 Scarcity and effort signaling: Descriptive statistics

	All	Baseline	Scarcity	Transparency	Scarcity x Transparency
Mean	€7.45	€4.22	€8.44	€7.88	€9.50
Median	€1.00	€1.00	€1.42	€1.00	€4.50
SD	€13.65	€7.08	€14.61	€13.22	€17.33
Fraction €0.00 bids	40.3%	46.0%	38.5%	41.5%	35.1%
Top 5th percentile	€52.68	€27.21	€57.83	€53.18	€67.08
Top 10th percentile	€39.58	€22.24	€43.91	€40.71	€48.10
Top 20th percentile	€27.60	€16.03	€31.24	€28.75	€33.32
N	870	235	218	195	222

Notes. Averages of willingness to pay in the top 5th, 10th and 20th percentile are provided.

Our findings support both the scarcity and transparency hypotheses. The average bid in the scarcity and transparency treatments are respectively 100% and 86.7% higher than in the baseline treatment. We employ the nonparametric Mann-Whitney U test to determine whether the distribution of two independent groups of bids differ significantly from each other. We find that the scarcity treatment differs significantly from the baseline treatment (Mann–Whitney $U = 21926.5$, $p < 0.01$, two-tailed). Figure 2 shows that the demand curve of the scarcity treatment is to the right of the demand curve of the baseline treatment. Note that this treatment effect seems more pronounced in the higher percentiles as illustrated in Figure 2. We also find that the operational transparency treatment differs significantly from the baseline treatment (Mann–Whitney $U = 20060$, $p < 0.05$, two-tailed). Scarcity signaling and operational transparency are also significant in a Tobit regression (see Model 1 in Table 2). We do not find support for an interaction effect (see Model 2 in Table 2).

Table 2 Scarcity and effort signaling: Tobit regression on willingness to pay

	Model 1		Model 2	
	Estimate (st. err.)	t	Estimate (st. err.)	t
Scarcity	469.13 (142.96)	3.28^{***}	637.00 (199.24)	3.20^{***}
Transparency	341.85 (142.82)	2.39^{**}	521.51 (205.93)	2.53^{**}
Scarcity x Transparency			-345.40 (285.37)	-1.21
Intercept	-270.61 (125.56)	-2.16^{**}	-352.96 (143.50)	-2.46^{**}
N	870		870	
N (censored at €0)	351		351	

Notes. $^{**}p < 0.05$; $^{***}p < 0.01$.

3.2 Mail-in rebates

A well-known marketing tactic is to provide after-purchase discounts. Mail-in rebates are a common example (Thaler, 1985; Ault *et al.*, 2000). After purchase, the buyer is required to fill out a form with proof of purchase and to use the postal service to mail it back to receive the rebate. Besides the positive effect on sales, manufacturers also profit from ‘slippage’, i.e., some buyers not returning the rebate form in time.

A manufacturer who plans to employ mail-in rebates will have to decide on (a) the magnitude of the rebate and (b) rebate spending restrictions. A rebate that is too low might not lead to an increase in sales and, thus, would not offset the cost of the rebate program. At the same time a rebate that is too high can result in considerable losses. A rebate in the form of cash is the least restrictive but does not guide buyers to spend the rebate in a way that can benefit the manufacturer. However, imposing spending restrictions might decrease the attractiveness of the rebate if these are perceived as too restrictive.

We conducted an online experimental auction to study the extent to which the magnitude of a rebate affects WTP and whether imposing rebate spending restrictions decreases WTP. The experiment consists of a baseline treatment combined with a 2 (Low rebate amount, High rebate amount) x 2 (No restrictions, Spending restrictions) between-subject factorial design. The focal product is a facial cleansing device that uses a rotating brush to scrub the facial surface. In the baseline treatment, the device is offered without a rebate. The low and high rebate amounts are operationalized as €15 and €30 respectively. A pure cash rebate is offered in the treatments without spending restrictions. In the treatment with spending restrictions the rebate is offered in the form of a gift card. The gift card can only be spent at a well-known cosmetics retail chain in the Netherlands.

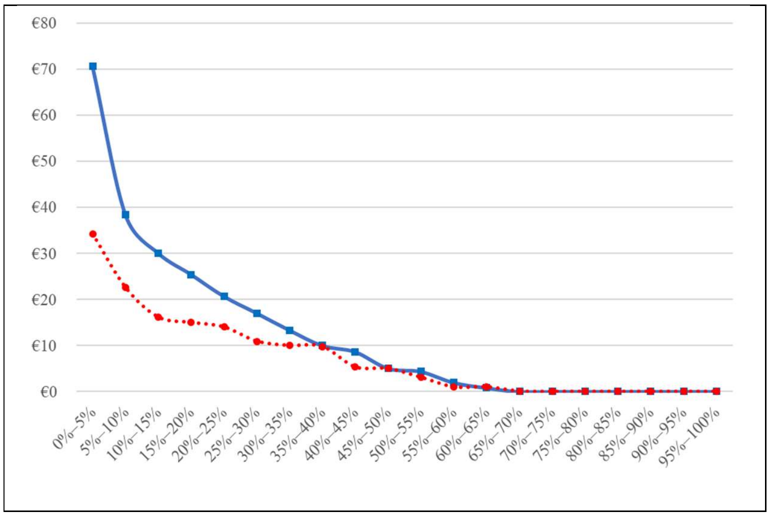
Table 3 Mail-in rebates: Descriptive statistics

	All	Baseline	€15 Gift card	€30 Gift card	€15 Cash rebate	€30 Cash rebate
Mean	€11.28	€7.37	€10.83	€11.59	€11.21	€15.49
Median	€5.00	€5.00	€5.00	€5.00	€5.00	€5.00
SD	€17.07	€9.27	€14.54	€17.45	€17.05	€23.44
Fraction €0.00 bids	34.4%	32.8%	32.3%	35.0%	35.8%	36.3%
Top 5th percentile	€64.65	€32.93	€50.71	€65.03	€56.76	€87.14
Top 10th percentile	€49.79	€28.00	€40.86	€50.75	€46.05	€69.38
Top 20th percentile	€37.59	€21.77	€33.01	€38.72	€36.34	€53.71
N	637	128	133	143	109	124

Notes. Averages of willingness to pay in the top *5*th, 10th and 20th percentile are provided.

The descriptive statistics suggest that WTP is substantially higher in the rebate treatments than in the baseline treatment. However, the demand curves only diverge for prices above the median. Figure 3 shows that the combined effect of rebates is only noticeable in the upper half of the demand curves and that the rebate effect becomes more pronounced in the higher percentiles. In particular, the median value nor the fraction of zero bids differ significantly across treatments ($\chi^2(4) = 0.345$, $p = 0.99$).

Figure 3 Mail-in rebates: Demand curves



Notes. The demand curve with round/square data points represents the baseline treatment (n = 128)/all four rebate treatments combined (n = 509).

Table 4 contains Tobit regressions to analyze the data further. Model 1 confirms that the rebate treatments combined result in a higher WTP compared to the baseline treatment. Model 2 explores to what extent the rebate amount affects WTP. We find that even though WTP increases in the low rebate amount treatments, it is not significantly higher than in the baseline treatment that does not have a rebate. However, we do find that WTP is significantly higher in the high rebate amount treatments than in no rebate amount treatment. Model 3 explores to what extent spending restrictions affect WTP. Compared to the baseline treatments, the use of a gift card does not significantly increase WTP as it comes with strict spending restrictions. Cash, however, does increase WTP significantly as hypothesized.

Table 4 Mail-in rebates: Tobit regression on WTP

	Model 1		Model 2		Model 3	
	Estimate (std. err)	t	Estimate (std. err)	t	Estimate (std. err)	t
Rebate present	512.16 (242.83)	2.11**				
Low rebate amount			387.65 (267.74)	1.45		
High rebate amount			625.35 (263.33)	2.36**		
Gift card					416.31 (262.02)	1.59
Cash rebate					626.33 (269.60)	2.32**
Intercept	148.81 (218.71)	0.68	150.07 (218.30)	0.69	149.86 (218.37)	0.69
N	637		637		637	
N (censored at €0.00)	219		219		219	

Notes. The baseline treatment is the treatment without any rebate. $^{**}p < 0.05$; $^{***}p < 0.01$.

3.3 Brand equity

A major methodological challenge within the marketing literature is finding measures of consumers' attitude towards brands that correlate with purchase behavior. From a managerial point of view, knowing consumers' attitude towards a brand might be an early predictor of revenue growth. A prominent example of such a measure is the Net Promoter Score (NPS), which consists of a single question asking "How likely is it that you would recommend [a brand, a product, a service, etc.] to a friend or colleague?" (Reichheld, 2003). Respondents are asked to answer this question on a Likert scale ranging from 0 ("not at all likely") to 10 ("extremely likely"). The NPS is defined as the fraction of promoters minus the fraction of detractors, where promoters [detractors] are respondents whose ratings are 9 or 10 [at most 6]. Although the NPS is used extensively in various industries, scholars have argued that there is little evidence to support the notion that NPS is a superior predictor of revenue growth (Keiningham *et al.*, 2007).

We explore the use of experimental auctions to provide a behavioral measure of brand equity. Specifically, gift cards are auctioned to measure consumers' attitude towards brands. The use of gift cards restricts the purchase to a specific brand but without requiring the buyer to commit to a specific product. This fungibility allows for the possibility to measure consumers' attitude towards a brand in an incentivized manner. Arguably, measuring how much consumers are willing to pay to for a gift card reveals either how much they are planning to spend at a specific brand or whether they know someone who would value to buy something from that brand to whom they can give the gift card.

There is a natural ceiling to how much consumers are prepared to pay for a gift card, which is the gift card's nominal value. It should be noted, however, that the fact that gift cards are usually sold at the nominal value implies that consumers' WTP for gift cards can exceed the nominal value. A common explanation for this phenomenon is that due to social norms consumers refrain from gifting cash and, thus, prefer a medium that is not perceived as cash but yet is fungible as cash (Offenberg, 2007). Because the recipient is free to choose how to spend the gift card, the amount of deadweight loss is minimized. Offenberg (2007) argues that the resale value of a gift card can reveal how much a brand is valued. She explores the resale value on the auction website eBay and finds that, on average, the resale value of a Wal-Mart gift card exceeded 85% of the nominal value while for the fashion retailer Express this was below 75%.

For the current case study, we selected five well-known Dutch retail brands: Wehkamp, Mediamarkt, Coolblue, Bol.com and Bijenkorf. All five retail brands sell online and ship nationwide. Of these five, two do not have brick-and-mortar stores: Wehkamp and Bol.com. We invited participants to an experimental auction in which they got the chance to bid on a gift card to spend at one of these five retail brands, randomly selected. The nominal value of the gift card was kept constant at €50. The participants were also asked to answer the question "How likely is it that you would recommend [the retail brand] to a friend or colleague?” on a Likert scale ranging from 0 (“not at all likely”) to 10 (“extremely likely”).

Table 5 Brand equity: Descriptive statistics

	All	Wehkamp	Mediamarkt	Coolblue	Bol.com	Bijenkorf
Mean	€17.64	€14.46	€18.38	€16.48	€19.72	€18.96
Median	€17.50	€10.00	€20.00	€15.00	€20.00	€20.00
SD	€13.57	€11.93	€12.95	€14.29	€13.21	€14.86
Fraction €0.00 bids	13.9%	17.4%	10.1%	17.9%	9.4%	15.6%
Top 5th percentile	€46.23	€40.91	€44.85	€47.15	€46.77	€47.28
Top 10th percentile	€42.88	€36.50	€41.99	€43.24	€43.62	€45.05
Top 20th percentile	€37.74	€32.23	€36.94	€38.29	€38.64	€40.97
N	1113	218	237	212	235	211

Notes. Averages of willingness to pay in the top 5th, 10th and 20th percentile are provided.

The data from this experiment shows that for all brands, both the means and medians of the bids are much lower than the nominal value of the gift card (Table 5). The percentage of zero bids is much lower than in the previous two case studies, though, which means that gift cards are more likely to be of some value than a specific product, as expected. Less obvious is why on average 13.9% of the participants bid zero taking into account that the nominal value is €50. Possible explanations are (a) lack of cash, (b) high perceived transaction costs combined with a low WTP, and (c) unfamiliarity with the retail brand.

The theory of NPS distinguishes three groups based on their response to the recommendation question: Promoters (10 – 9), Passives (8 – 7) and Detractors (6 – 0). Figure 4 shows the demand curve of each group with the Promoters having the highest demand curve, followed by the Passives and the Detractors. This order is consistent with the assumption underlying NPS that the likelihood that Promoters [Detractor] have a greater [smaller] likelihood to induce future sales than Passives.

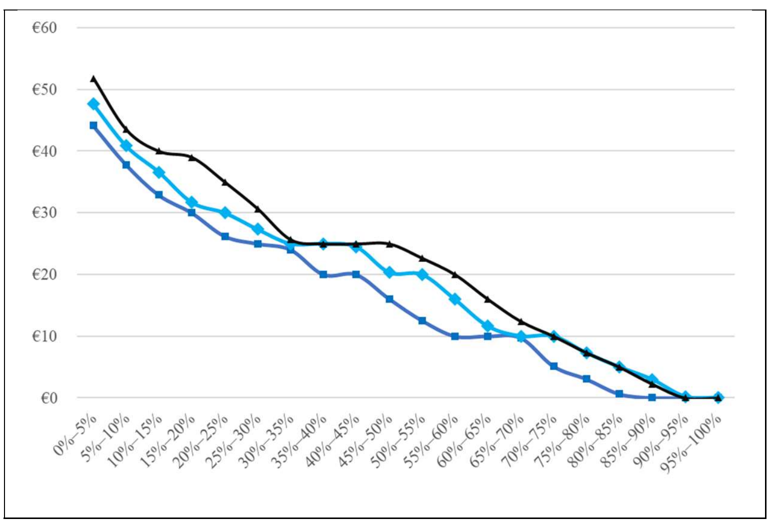
Indeed, Promoters and Passives are, on average, willing to pay significantly more than Detractors (Model 2 in Table 6). Moreover, significant differences in WTP between retail brands remain even when correcting for the group to which respondents belong (Model 2 in Table 6). This implies that NPS alone is not sufficient to fully explain consumers' purchase intent towards a brand.

Table 6 Brand equity: Tobit regressions on WTP

	Model 1		Model 2	
	Estimate (std. err)	*t*	Estimate (std. err)	*t*
Bol.com	604.37 (145.07)	4.17***	488.14 (146.55)	3.33***
Bijenkorf	479.73 (149.38)	3.21***	464.03 (148.21)	3.13***
Mediamarkt	463.07 (144.85)	3.20***	418.66 (144.06)	2.90***
Coolblue	204.65 (149.51)	1.37	185.34 (148.35)	1.25
Promoter			531.20 (155.17)	3.42***
Passive			359.15 (112.98)	3.18***
Intercept	1299.10 (105.14)	12.36***	1205.73 (106.95)	11.27***
N	1113		1113	
N (censored at €0)	155		155	

Notes. Wehkamp is the baseline treatment. Detractors is the baseline NPS group. $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 4 Brand equity: Demand curves



Notes. The curve with triangle/diamond/square data points represents the demand curve of the Promoters (n = 116)/Passives (n = 244)/Detractors (n = 749).

3.4 Innovation marketing

Innovation marketing is key in promoting sustainably produced new products. This case study focuses on consumer acceptance of products that are processed using electroporation technologies. Electroporation is a preservation method that evolved from processes found in nature like the electricity pulses emitted by electric eels. Electroporation for human food processes goes back to at least Prochownick and Spaeth (1890) who studied effects of electric currents on bacteria.[16] Commercial applications include liquid and semiliquid food products, such as fruit juices, soups, and liquid eggs. Reported advantages of electroporation relative to traditional methods like heating include decreased energy use, longer shelf lives, and retaining the food's fresh characteristics like color, flavor, nutritional values, and sensory properties.[17] Despite these advantages, the uptake by the food industry has occurred less broadly than initially anticipated.[18]

While food scientists applaud the technological superiority of novel food technologies (NFTs) like electroporation over traditional methods, consumers tend to be conservative and are hesitant to switch. For example, consumer skepticism prevented the industry to take up irradiation successfully and lead to a considerable delay to the large-scale introduction of genetically modified food. In research about consumer and industry acceptance of novel food technologies commissioned by the Irish Department of Agriculture, Food & the Marine, Henchion et al. (2013) observe that "the processes of forming and changing attitudes towards NFTs are complex and dependent on characteristics of the individual and the technology, and are impacted by the types and forms of information provided."

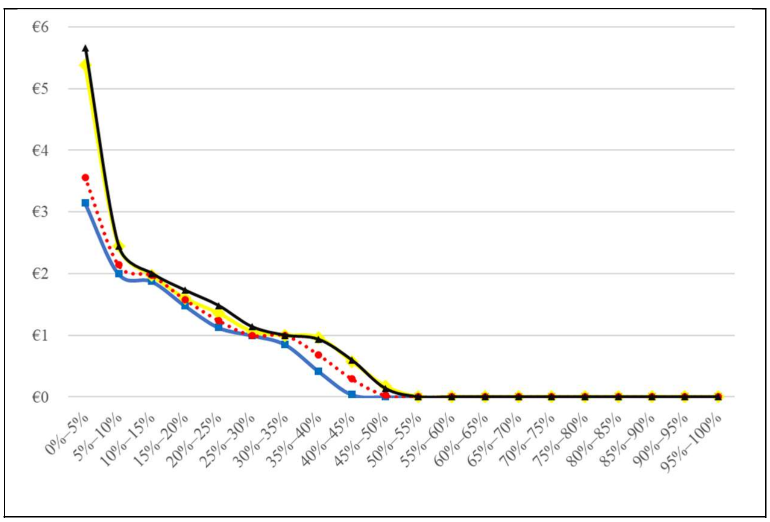
To examine how advertising different characteristics of electroporation affect consumer demand, we selected a fruit juice that is sanitized using electroporation. To nudge consumers towards consuming the juice, it is vital to know how different properties of this promising technology affect consumer demand. To address this question, we ran experimental auctions to estimate the effect on WTP of the

[16] See Jaeger et al. (2015) for a historical development of electroporation.
[17] Guo et al. (2014).
[18] Troy et al. (2016).

following production technology characteristics: (i) the production technology using electricity for sanitation, (ii) the sustainability of the new technology, and (iii) the increased product quality.

The experiment exploits 4 treatment conditions that were varied in a between-subject design. The baseline treatment (treatment 0) consists of an advertisement with a picture of the fruit juice and specifications about production technology characteristics. The $ENVIRON$ treatment (treatment 1) emphasizes the environmental benefits of using the MEF technology. The $QUALITY$ treatment (treatment 2) stresses the increased quality (better taste, increased shelf life) of the product due to the MEF technology relative to heating. The $ELECTRICITY$ treatment (treatment 3) highlights the fact that the juice is produced using electric waves to kill bacteria. For our experiment, we invited a representative sample from the Dutch population. 1,568 of those invited completed the flow, which constitutes the final sample used for analysis.

Figure 5 Innovation marketing: Demand curves



Notes. The curve with round/diamond/triangle/square data points represents the demand curve of the baseline/*ENVIRON*/*QUALITY*/*ELECTRICITY* treatment (n = 392 per treatment).

Figure 5 presents the aggregated demand curve and Table 7 provides descriptive statistics. It is worth noting that, different from the other case studies, the demand curves for all treatments are closely approximated by exponentially distributed WTPs. Comparing the means as well as the top 5th, 10th , and 20th percentiles across treatments, we observe WTP to be larger when the quality and environmental benefits of the product are emphasized in comparison to the baseline, while it is lower when the production technology is emphasized.

Table 7 Innovation marketing: Descriptive statistics

	All	Baseline	$ENVIRON$	$QUALITY$	$ELECTRICITY$
Mean	€0.74	€0.68	€0.83	€0.86	€0.60
Median	€0.00	€0.00	€0.01	€0.01	€0.00
SD	€1.28	€1.05	€1.41	€1.58	€0.99
Fraction €0.00 bids	50.5%	50.0%	49.5%	48.2%	54.1%
Top 5th percentile	€4.44	€3.56	€5.38	€5.66	€3.15
Top 10th percentile	€3.37	€2.87	€3.95	€4.09	€2.49
Top 20th percentile	€2.75	€2.58	€3.31	€2.98	€2.13
N	1568	392	392	392	392

Notes. Averages of willingness to pay in the top 5th, 10th and 20th percentile are provided.

To formally compare the treatments in terms of WTP, we make use of the property that in the case of exponentially distributed WTPs, the optimal mark-up equals the distribution's rate parameter (see Section 2.3). For each treatment t, we estimate the corresponding rate parameters λ_t using the following regression model:

$$w_t^{(i)} = -\lambda_0 log\left(1 - \widehat{F}_t(w_t^{(i)})\right) - \sum\nolimits_{\tau=1}^{3} (\lambda_\tau - \lambda_0) log\left(1 - \widehat{F}_t(w_t^{(i)})\right) I\{\tau = t\} + \varepsilon_{it},$$

$$i = 1, \ldots, 157, t = 0,1,2,3,$$

where $\widehat{F}_t$ is treatment t's empirical distribution of the bids submitted and I is the indicator function. We only use the 40% highest bids. The reason for doing so is that the lowest WTP levels are irrelevant for the optimal price, so that it is more important to estimate the right tail of the distribution precisely than the complete distribution.

The regression results are in Table 8. First, notice that the regression's R^2 without controls equals 0.9082, suggesting that the estimated WTP distributions are quite accurate. Moreover, both treatments *ENVIRON* and *QUALITY* yield significantly higher estimates for λ_t than the control treatment. The treatment *ELECTRICITY* yields a significantly lower estimate for λ_t than the control treatment. We conclude that in marketing campaigns for MEF-produced products the environmental and quality benefits should be emphasized, in contrast to the electricity-based sanitation method.

Table 8 Innovation marketing: Predicted Rate Parameters

	Model 1		Model 2	
	Estimate (std. err)	*t*	Estimate (std. err)	*t*
λ_0	122.55 (3.24)	37.77***	121.91 (3.40)	35.78***
$\lambda_{ENVIRON} - \lambda_0$	21.82 (3.29)	6.63***	22.26 (3.32)	6.70***
$\lambda_{QUALITY} - \lambda_0$	30.62 (3.29)	3.90***	30.98 (3.31)	9.35***
$\lambda_{ELECTRICITY} - \lambda_0$	-9.61 (3.29)	-2.92***	-9.31 (3.32)	-2.81***
Intercept	-75.48 (3.29)	9.30***	-66.24 (14.17)	-4.67***
Controls	None		Demographic Controls	
N	628		628	

Notes. The baseline treatment is the treatment with the overall description. $^{**}p < 0.05$; $^{***}p < 0.01$.

4. Discussion and Conclusion

In this paper, we have discussed the use of online experimental auctions for demand elicitation. Experimental auctions, based on the (multi-unit) Vickrey auction, are a promising demand-elicitation method because they are incentive compatible and non-hypothetical in contrast to traditional methods like focus groups, surveys, market tests, laboratory pre-test markets, and conjoint analysis. While most research on experimental auctions relies on laboratory experiments, more recently, experimental auctions in the field have become increasingly important. We have discussed how the experiments can be designed to foster external and internal validity and we have shown how online experimental auctions can be used to study marketing questions related to communicating scarcity of supply, providing after-purchase discounts, consumer attitudes towards brands, and innovation.

So far, online experimental auctions have been mainly used to measure WTP for single items. Future research can reveal to what extent they have a broader potential in that they can also be used to measure WTP for multiple items, to measure willingness-to-accept (WTA), or for direct commercial purposes. We elaborate on these extensions below.

The Vickrey auction can be generalized to let consumers express their WTP for sets of multiple items in an incentive-compatible way. In its most general form, the auctioneer simultaneously auctions several, potentially heterogeneous, items. The consumers are asked to express their WTP for all subsets of the items. For example, if two items A and B are auctioned, the consumer submits a bid on item A, one on item B, and one on the bundle AB. Similarly, if n items of a homogeneous product are auctioned, the consumer can submit bids for $1, 2, \dots, n$ units. After receiving the bids from all consumers, the auctioneer assigns the items over the consumers in such a way that surplus among the consumers is maximized assuming that all consumers truthfully reveal their WTP for all subsets. Each bidder pays an amount equal to the opportunity costs she imposes on the other bidders, i.e., the difference between the surplus the auction generates in her present and the surplus the auction would generate if she had not participated in the auction. The resulting Vickrey-Clarke-Groves mechanism could be used to measure the extent to which products are substitutes or complements and, in turn, how the seller can optimally employ bundling strategies. The downside is that it may not be straightforward for bidders to understand that it is in their best interest to fully reveal their WTP for each subset of items.[19] In some settings, it might be better to auction different subsets of the items in separate auctions to different groups of consumers like in the bundling case study.

[19] Whether bidders tend to bid truthfully depends on the context. Porter and Vragov (2006) find significant overbidding in the multi-unit Vickrey auction in which two bidders compete for two homogeneous items.

Online experimental auction platforms can also be used to measure consumers' minimum WTA for giving up consumption goods. This extension would allow measuring the monetary value of possessions and access rights (e.g., Acquisti *et al.*, 2013). For example, to study to what extent consumers value their social media profiles, participants are asked to submit a bid that reflects the minimum amount that they would accept to delete or temporarily give up their social media profiles. Participants with the lowest bids are the winners and will receive the $(n+1)$th lowest bid as compensation for their sacrifice.

Online experimental auctions may also be interesting from a direct commercial point of view. The multi-unit Vickrey auction allows sellers to choose a price to maximize either revenue or profits using the elicited bids to calculate expected auction revenue. Baliga and Vohra (2003) show that if the number of bidders is large, bidding value remains a weakly dominant strategy even though the number of items sold is endogenous. As a consequence, the bids not only serve the purpose of profit maximization in the current auction but they also render valuable information about demand that entrepreneurs can use for future commercial activities.

Declarations

The authors have no conflict of interest.

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Appendix A: Experimental design case studies

Case Study: Scarcity and effort signaling

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Treatment: *Baseline*

Translations

Header: Amsterdammertje
Green circle: For example for in your garden
Description: Measurements
Height 1.15 meters
Diameter 162 milimeters
Weight 20 kilograms
Disclaimer: ATTENTION: The *Amsterdammertje* has stood in the streets for many years and , as a result, is slightly damaged (scartches, rust, peeling paint).
</td>
<td>
Treatment: *Scarcity*

Translations

Manipulation: All *Amsterdammertjes* will be removed from the street scene. Grab your chance to buy one before it’s too late.
</td>
</tr>
</table>

Treatment: *Transparency*

Translations

Manipulation: It took a bit effort but we managed to get it out of the ground… (With permission from the municipality.)

Treatment: *Scarcity x Transparency*

Translations

Manipulation: All *Amsterdammertjes* will be removed from the street scene. Grab your chance to buy one before it's too late.

It took a bit effort but we managed to get it out of the ground… (With permission from the municipality.)

Case study: Mail-in rebates

Treatment: *Baseline*

Translations

Rectangle: VisaPure
Facial Cleansing Brush
Deep, mild cleansing
Header: VisaPure
Subheader: Deep, mild cleansing for a soft and glowing skin
Claim: 10x more effective than manual cleansing

Treatment: *Gift card €15*

Translations

Treatment: *Gift card €30*

Translations

<table>
<tr>
<td>Promotion: Including a €15 Douglas gift card with the purchase of this product</td>
<td>Promotion: Including a €30 Douglas gift card with the purchase of this product</td>
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<td>Treatment: Cash rebate €15

Translations

Promotion: Receive €15 on your bank account after purchasing this product</td>
<td>Treatment: Cash rebate €30

Translations

Promotion: Receive €30 on your bank account after purchasing this product</td>
</tr>
</table>

Case study: Brand equity

Cadeaukaart t.w.v. €50,-

Treatment: *Wehkamp*

Translations

Gift card: At your service
Description: Gift card with a value of €50

Cadeaukaart t.w.v. €50,-

Treatment: *Mediamarkt*

Translations

Gift card: —
Description: Gift card with a value of €50

Cadeaukaart t.w.v. €50,-

Treatment: *Coolblue*

Translations

Gift card: Gift
Everything for a smile
Description: Gift card with a value of €50

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Cadeaukaart t.w.v. €50,-
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Cadeaukaart t.w.v. €50,-
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<td>
Treatment: *Bol.com*

Translations

Gift card: Gift card
Chock full stores, full of discount
Description: Gift card with a value of €50
</td>
<td>
Treatment: *Bijenkorf*

Translations

Gift card: Gift card
Description: Gift card with a value of €50
</td>
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Case Study: Production Technology Characteristics

Treatment: *Benchmark*

Translation:
New pasteurization technology

- electric shocks instead of heating
- less energy and water waste
- vitamins, smell, color and taste remain
- can be kept longer

Treatment: *ENVIRON*

Translations of highlighted text:
Produced with 30% less energy and water

Treatment: *ELECTRICITY*

Translations of highlighted text:

Produced with electric shocks to kill bacteria

Treatment: *QUALITY*

Translations of highlighted text:

Healthier and tastier
Stays fresh for 31 days