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Curious about the price?

Consumers' behavior in price reveal auctions

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Abstract

We exploit several specific features of a recent online selling mechanism, the so-called price reveal auction, to empirically investigate how consumers' behavior changes in response to an item's intrinsic characteristics and 'social attributes'. We document a significant effect of the item's brand and intended use (outdoor vs. indoor) in influencing an agent's degree of impatience and willingness to pay. We show that, while both variables have some explanatory power when considered in isolation, it is their interaction that really matters. We also study the determinants of the mechanism's profitability and show how, in the context of a price reveal auction, the sale of positional goods may backfire and harm revenues.

JEL Classification: D44, D12.

Keywords: price reveal auction, willingness to pay, social attributes, positional goods.

1 Introduction

In this paper we provide the first empirical analysis of a recent online selling format, the so-called price reveal auction (PRA). We investigate the profitability of the mechanism and draw some more general conclusions about consumers' behavior in online markets. In

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particular, by exploiting several peculiar features of the mechanism, we show how agents' price sensitivity and willingness to pay are influenced not only by the physical characteristics of the item on sale but also by (the interaction of) some of its 'social attributes', namely the brand and the degree of public visibility.

In a PRA, the current price of the item on sale is hidden. Participants can privately observe the price if and only if they pay the seller a fee $c > 0$. An agent who observes the price must then decide whether or not to buy the item. If the agent buys the item, the auction closes. If the agent does not buy the item, the price goes down by a predetermined amount $\Delta < c$ and the auction continues. A PRA thus differs from a standard descending price auction (see Krishna, 2002) in two fundamental aspects. First, the current price of the item is not publicly observable. Second, the price does not fall exogenously as a function of time but rather endogenously in response to participants' behavior.

The following example illustrates the functioning of the PRA mechanism in more detail. The example was taken from the website Bidster.com, which was the first website to use the PRA format.[1] The mechanism was then adopted by a number of competitors.[2]

"*The market price of the product is* \$100. *Starting price for the auction is* \$95 *(the starting price is hidden for the participants). Every scratch lowers the price by* \$2.5. *When the auction starts, Maria scratches the auction and gets the current price of* \$92.50. *She sees the price in* 10 *seconds, but thinks it is a bit expensive and chooses not to buy the product for the current price. Thereafter, Peter scratches the auction and gets his current price of* \$90. *He also thinks it is a bit expensive and decides not to buy the product. [...] . Maria scratches the auction again and gets the current price* \$85.00. *She thinks it's a good price and chooses to purchase the product. Then the auction ends and Maria is the winner.*"

We tracked the website Bidster.com for approximately 16 months and assembled a unique dataset including detailed information about *all* 134 PRAs that reached a conclusion (i.e., all auctions in which the item was sold). Our empirical analysis leads to two sets of results. First, we estimate the determinants of the mechanism's profitability and of the level of agents'

[1]See http://web.archive.org/web/20110728105824/http://www.bidster.com/page/how-it-works?. Notice that, in the jargon of the website, "to scratch the auction" means "to observe the price". Bidster.com launched PRAs in December 2009. Following legal controversies, the website closed down in April 2011.

[2]PRAs are currently implemented by a number of websites, such as http://u-wantit.com/, http://1250auctions.com/ (both in English), http://ambetion.com/ (in Spanish), and https://www.youbid.nl (in Dutch). PRAs are sometimes also labelled "scratch auctions", "express auctions", or "reverse auctions".

participation. We find that the PRA format generates an average profit margin of 36%. Profits tend to be larger in auctions with more valuable goods; expensive items attract a larger number of price observations which, through the accrual of the associated bidding fees, are the main source of revenue for the seller. However, and perhaps surprisingly, we find that the size of the bidding fee does not have a significant impact on profits. We then rationalize this result by showing how an increase in the bidding fee triggers two opposite effects that basically cancel out. First, a large fee raises the marginal revenue generated by every single price observation. Second, a large fee reduces the level of participation in a non-random way. In particular, auctions with large fees only appeal to those agents who are particularly eager to buy the item (i.e., those with a high willingness to pay). These agents are thus more likely to buy the item (and thus end the auction), no matter the price they observe. As a result, the auction attracts a lower number of price observations. We consider these results to be important because, beyond their current commercial use, PRAs can also be used in other contexts, such as charity events or fund-raising activities (see, for instance, Engers and McManus, 2007).

The second set of results are more general, as they document differences in agents' attitudes towards specific types of products and/or brands. In particular, we exploit substantial heterogeneity in the duration of the auctions and in the size of the final discount (i.e., the difference between the retail price and the price the winner pays) to make several inferences about consumers' eagerness to obtain certain goods. This heterogeneity stems from how players deal with the key trade-off that characterizes the PRA. On the one hand, the longer an agent waits, the more likely the price will fall by a substantial amount (because rival agents will observe the price).[3] On the other hand, the longer an agent waits, the more likely the auction will close (because someone else buys the item).[4]

Clearly, the way participants solve this trade-off may vary across different auctions on the basis of the characteristics of the item on sale. Consider for instance two PRAs that offer two items that have the same retail price. However, auction 1 sells an item that consumers perceive as 'special', perhaps because it is fashionable and increases the owner's social status, whereas auction 2 offers a non-positional good. The agents' willingness to pay will be higher in auction

[3]Notice that, because of the condition $\Delta < c$, the marginal benefit of observing the price (the price cut Δ) is smaller than the marginal cost (the fee c). As such, a participant who is looking for a deal must necessarily free-ride on his rivals.

[4]In this respect, a PRA can thus be classified as a preemption game (see Rosenthal, 1982).

1, and this in turn increases the risk of being preempted by a rival. Such an intuition leads to two testable predictions. First, auction 1 will likely end *before* auction 2. Second, auction 1 will likely attract a *lower* number of price observations, thus leading to a *lower* discount and to *lower* profits for the seller. This second result may seem counterintuitive, because fashionable items should stimulate the agents' level of participation, which should benefit the seller. However, and exactly because of the specific rules of the PRA, the participants' eagerness to win the item implies that an agent that observes the price will likely buy the item. Given that the auction closes as soon as someone buys the item, the *actual* number of price observations in auction 1 is likely to be smaller than in auction 2, even though auction 1 may attract more (potential) participants than auction 2.

Our empirical analysis confirms these results. We find that PRAs that offer items that increase the owner's status (see Rege, 2008) or self-image (see Johansson-Stenman and Martinsson, 2006) generate a lower number of price observations, sell the item at a lower discount, and produce lower profits. We also find that the real driver of these effects is not the brand effect *per se,* but rather the interaction between the brand effect and the intended use of the item: when the positional good is an outdoor product, external visibility increases and so does the saliency of the item's social attributes.[5] Our findings are consistent with results from a number of previous studies on conspicuous consumption and brand effects. In particular, it has been shown that consumers' willingness to pay is higher for positional goods (Bagwell and Bernheim, 1996), that status considerations and brand credibility decrease price sensitivity (Goldsmith *et al.*, 2010, Erdem *et al.*, 2002), and that consumers show a clear distinction between brand names perceived to confer different levels of status (O'Cass and McEwen, 2004).

This paper is organized as follows. Section 2 provides a simple theoretical framework that guides the empirical analysis. Section 3 describes the dataset and implements the main empirical analysis. Section 4 collects a series of robustness checks. Section 5 presents the conclusions.

[5]An example of a positional item that combines high intrinsic characteristics and outdoor visibility is the Apple iPhone. An example of an item with high intrinsic characteristics but no outdoor visibility is an Apple iMac. Indeed, both goods often appear in our dataset.

2 Theoretical background

In this section, we sketch a very simple formalization of the PRA mechanism.[6] The purpose of the model is to highlight the determinants of the seller's profits and thus serve as the basis for the empirical analysis. Consider a PRA for a generic item with retail price p_{ret}. The seller sets the starting price $p_{start} = \alpha p_{ret}$ with $\alpha \in (0, 1]$. The retail price p_{ret} is common knowledge among all participants, whereas α, and thus p_{start}, is the seller's private information. Let $N = \{1, ..., n\}$ be the set of potential participants and $\eta_i (c, p_{ret}, \mathbf{x})$ be the number of times that agent $i \in N$ observes the price throughout the auction. We postulate that $\eta_i (\cdot)$ is a function of three factors: the amount of the fee c that an agent must pay every time he/she observes the price; the item's retail price p_{ret}; and product-specific characteristics $\mathbf{x}$ that are not captured by the retail price. In particular, the vector $\mathbf{x}$ captures the item's social attributes such as the brand, the capability to confer social status to the owner, and the degree of external visibility. We expect a negative sign for the marginal effect of c on $\eta_i (\cdot)$, whereas we are ex-ante agnostic about the signs of the marginal effects of p_{ret} and of the $\mathbf{x}$ attributes.

Whenever an agent that observes the price decides not to buy the item, the price falls by the amount $\Delta = \beta c$ (the parameter $\beta \in (0, 1)$ is common knowledge). Thus, the final selling price p_{fin} can be formulated as

$$p_{fin} = p_{start} - \eta (c, p_{ret}, \mathbf{x}) \cdot \Delta \tag{1}$$

where $\eta (c, p_{ret}, \mathbf{x}) = \sum_{i \in N} \eta_i (c, p_{ret}, \mathbf{x})$ denotes the total number of times that the price was observed. Profits are then given by

$$\pi = p_{fin} - v_s + \eta (c, p_{ret}, \mathbf{x}) \cdot c \tag{2}$$

where v_s indicates the valuation of the seller. In general, one may presume that $v_s < p_{ret}$, since it is likely that, because of bulk orders or marketing reasons, the seller bought the item

[6]See Gallice (2015) for a full theoretical analysis of the PRA format. In general, PRAs belong to the family of so-called 'pay-per-bid auctions' which also includes penny auctions and lowest unique bid auctions (LUBAs). In a penny auction (see Augenblick, 2015, Hinnosaar, 2014, and Platt *et al.*, 2013), each bid increases the current price by a fixed amount (a penny) and restarts a public countdown; the winner is the participant who holds the winning bid when the countdown expires. In a LUBA (see Gallice, 2009, Houba *et al.*, 2011, and Östling *et al.*, 2011), participants place private bids and the winner is the agent who submits the lowest offer that is not matched by any other bid.

for less than the retail price. In this respect, both in the theoretical model and in the empirical analysis, we adopt a conservative approach (i.e., an approach that possibly underestimates the actual amount of profit) and set $v_s = p_{ret}$. By substituting equation (1) in (2), profits can thus be expressed as:

$$\pi = p_{start} - \eta\left(c, p_{ret}, \mathbf{x}\right) \cdot \Delta - v_s + \eta\left(c, p_{ret}, \mathbf{x}\right) \cdot c \tag{3}$$

Given that $p_{start} = \alpha p_{ret}$ and $\Delta = \beta c$, equation (3) becomes:

$$\pi = (\alpha - 1) \cdot p_{ret} + (1 - \beta) \cdot \eta\left(c, p_{ret}, \mathbf{x}\right) \cdot c \tag{4}$$

Equation 4 highlights the following relationships:

1) Profits are strictly increasing in α. In the empirical data that we will analyze, we do not observe α (i.e., we do not know the hidden starting price). However, equation 4 shows that the seller has incentives to set $\alpha = 1$. In line with this finding, we will base our main empirical analysis on the assumption that $\alpha = 1$. We will later show that all our qualitative results are robust to other specifications (in particular, and in line with the initial example, we will repeat the analysis with $\alpha = 0.95$).

2) Profits are affected by the item's retail price through two channels. First, p_{ret} may have a negative effect in case the seller sets $\alpha < 1$. Second, p_{ret} influences the number of price observations $\eta\left(\cdot\right)$ which in turn positively affects profits. Therefore, in this respect, $\frac{\partial \pi}{\partial p_{ret}}$ and $\frac{\partial \eta(\cdot)}{\partial p_{ret}}$ have the same sign. We will empirically estimate these two effects and find that indeed they are both positive and highly significant.

3) Profits are decreasing in β. We will not be able to test such a relationship, because in our sample β is constant across all auctions (in particular, in the data the condition $\beta = 0.5$ always holds).

4) Profits depend on $\mathbf{x}$ and, in particular, $\frac{\partial \pi}{\partial \mathbf{x}}$ and $\frac{\partial \eta(\cdot)}{\partial \mathbf{x}}$ have the same sign. Perhaps surprisingly, we find these effects to be negative, i.e., we find that some specific features of the item on sale (such as the fact of being a positional good) harm profits.

5) Profits are affected by the fee c through two channels. The first effect is direct and has a positive sign, as a larger c increases the revenues generated by every single price observation.

The second effect is indirect (it is mediated by $\eta(\cdot)$) and negative, as a larger fee depresses the total number of price observations. We find that these two effects basically cancel out: indeed, we document a net effect of c which is not significantly different from zero.

3 The Empirical Analysis

3.1 Data and Descriptive Statistics

We collected data about PRAs from the website Bidster.com. The website introduced the PRA format on the 29th of December 2009 and ceased its activities at the end of April 2011. During this period, Bidster.com was, by far, the market leader in the sector. We assembled a dataset containing publicly available information about *all* 134 PRAs that took place at Bidster.com. The heterogeneous items sold included smartphones, tablets, TV sets, computers, MP3 readers, electrical utilities, watches, and accessories.

For each auction, we retrieved, directly from the website, information about the item on sale, its current retail price (p_{ret}), the amount of the bidding fee (c), the amount of the price decrease (Δ), the final selling price (p_{fin}), and the opening and closing date and time. Because of the PRA rules, we could then easily reconstruct additional variables such as the number of price observations (η), the amount of the seller's profits (π), and the duration in hours of each auction (h).[7]

In order to assess whether possible differences in participants' behavior are related to specific characteristics of the item on sale, we introduce a classification which is based on a dual criterion. The aim is to try to disentangle the influence that social attributes of the item, such as the brand and the degree of public visibility, may have on the participants' willingness to pay. We thus introduce two indicator variables. The first one (*Apple*) takes value 1 if the item is an Apple-branded product. It is in fact widely recognized that Apple's success is largely based not only on the intrinsic quality of its products but also on the importance of the brand and on the social status it confers. The second indicator variable (*Outdoor*)

[7] The number of price observations η was obtained through the formula $\eta = (p_{ret} - p_{fin})/\Delta$ and profits calculated as $\pi = p_{fin} - p_{ret} + \eta \cdot c$. Remember that these calculations rely on two assumptions. First, we assume that the seller's valuation equals the retail price ($v_a = p_{ret}$). This assumption is probably very restrictive, as it is likely that the seller purchased the item for a lower price than the retail price. Therefore, estimated profits should be considered as lower bounds. Second, we assume that the starting price equals the retail price. This assumption is supported by the theoretical model described in Section 2 and will be further discussed in Section 4.

defines instead outdoor high-tech products such as smartphones, tablets and MP3 readers. We expect the positional aspects of these products to be more salient as outdoor products are more easily observed by others.

Table 1 reports descriptive statistics of the data. On average, participants observed the item's hidden price 403 times, with a significant variability in terms of standard deviation (437) and min-max range (3,591). This variability is due to the substantial heterogeneity in the economic value of the auctioned items: the average retail price is €443, with a minimum of €25 and a maximum of €1,700.[8] The average bidding fee c is approximately €1, whereas the price decrease Δ is always set as $\Delta = \frac{1}{2}c$. The mechanism's profitability is quite remarkable: the average profit amounts to €140, which is 36.5% of the average retail price. The bottom part of the Table shows descriptive statistics about the social attributes of the items. Both Apple and outdoor products are sufficiently represented in our data to allow for an analysis of consumers' behavior that hinges upon these variables. In particular, about 25% of the items are Apple-branded and 26% are outdoor products. The intersection of these two sets consists of approximately 19% of all auctioned items.

Unfortunately, a limitation of the dataset is that the data only allow for aggregate, i.e., auction level, analysis, as information at the individual level (say, agents' identities or their specific bidding histories) is not available. Despite this fact, it is possible to reproduce the history of each auction and obtain additional evidence on the potential determinants of an individual's purchase decision. We will further explore this point in Section 3.2.2.

3.2 The Econometric Model

3.2.1 Auction level analysis

The auction level analysis aims to understand the main determinants of the profits (π) and the total number of price observations (η). We thus estimate the following baseline equations:

$$\pi = \beta_0 + \beta_1 p_{ret} + \beta_2 c + \beta_3 Apple + \beta_4 Outdoor + \beta_5 Apple * Outdoor + \epsilon \qquad (5)$$

$$\eta = \gamma_0 + \gamma_1 p_{ret} + \gamma_2 c + \gamma_3 Apple + \gamma_4 Outdoor + \gamma_5 Apple * Outdoor + u \qquad (6)$$

[8] Descriptive statistics warn against the existence of potential biases in our estimation results due to the existence of possible outliers. We will more carefully investigate this issue in Section 4.

where p_{ret} represents the retail price, c is the bidding fee, *Apple* indicates Apple-branded products and *Outdoor* indicates products that are used in outdoor daily life. The interaction term $Apple * Outdoor$ allows us to capture the combined effect of being an Apple-branded product aimed at an outdoor use.

Ordinary least squares estimations of equations (5) and (6) are reported in Table 2 and Table 3. Columns (1) and (2) report the estimates for the effect of the retail price and the bidding fee; these two variables are expressed in logarithm so as to facilitate the interpretation of the coefficients. Columns (3) to (6) show the effects (in isolation) induced by the brand and intended use of the product. Column (3) highlights the Apple-brand effect, column (4) highlights the effect of products that are used in outdoor daily life, and column (5) shows the joint effect. Column (6) reports all three coefficients in the same model, therefore highlighting the prevalent determinant of the profits and number of price observations.

With regard to seller profits, the importance of the retail price in determining an auction's profitability stands out. The coefficient is positive, significant, and remarkably constant across all model specifications. A 1% increase in an item's retail price translates to an increase in the profit of almost €1. The amount of the bidding fee is positively related with profits, although the coefficient is small in magnitude and not statistically significant. This negligible effect is caused by the combination of two opposing effects (see the theoretical model in Section 2). On the one hand, a larger c positively influences profits, as it increases the marginal revenue generated by every price observation. On the other hand, a larger bidding fee discourages a participant from observing the price, unless the agent is highly interested in the item.[9] As a consequence, players that observe the price are likely to be characterized by a higher willingness to pay, and thus are ultimately more likely to buy the item. As such, the total number of price observations - the main source of profits for the seller - gets depressed (see Table 3 for evidence on the negative effect of c on η).

Table 2 also overviews the profitability associated with the social attributes of the item on sale. When considered in isolation, the variables *Apple*, *Outdoor*, and $Apple * Outdoor$ all explain a significant decrease in profits. The magnitude of these coefficients progressively increases (respectively, -31, -40, and -48). Moreover, the coefficient for the interaction term remains the only statistically significant one in the complete model. Indeed, the estimates of the complete model (see column 6) stress the role played by the positional nature of certain

[9]Section 3.2.2 provides further evidence on the role played by c.

goods. Notice in fact that the coefficient for Apple products shifts to a positive (albeit not significant) value when the variable that captures the level of external visibility is included. This indicates that the level of consumer impatience, and thus its consequences on profits, is not strongly influenced by the brand effect *per se*, but rather by the combination of brand and visibility.

Overall, all these results are in line with the intuition that we provided in the Introduction. An auction that offers an item that is widely known for both its intrinsic characteristics (i.e., high quality) and its positional aspects, certainly raises more interest than an auction that offers a low-quality good that conveys no status. However, in a PRA, the agents' excitement may backfire: the consumers' higher willingness to pay leads to an early closure of the auction, generating fewer price observations and thus lower profits.

The determinants of the number of price observations are analyzed in Table 3. The estimates show that monetary variables are significant predictors of the number of price observations. Both the coefficients for the retail price and for the bidding fee remain substantially stable across all model specifications. The effect of the retail price is positive and statistically significant. A 1% increase in the retail price translates to an increase in the number of price observations between 2.6 and 3. The effect of the bidding fee is similar in magnitude but opposite in sign because, in line with the law of demand, an increase in c lowers the number of price observations. The bottom panel of Table 3 displays the effects of the brand and the level of external visibility. The *Apple* coefficient is extremely high both in terms of absolute value and in statistical significance: on average, an Apple-branded product generates 143 price observations fewer than an item of a different brand. Even more pronounced is the *Outdoor* coefficient: in this case, a product that is mainly used outside the household generates 185 price observations fewer than an item which is used indoor. As before, the two effects reinforce each other: a PRA that sells an Apple product for outdoor use generates 204 less. However, the interpretation of these coefficients can be misleading when one considers each of the three variables in isolation. Indeed, the estimates of the complete model (see column 6) show that the coefficient for the interaction term (-151) remains the only statistically significant one. Once again, this indicates that it is not the product brand *per se* that influences participants' attitudes. The brand only matters when it confers status, i.e., only when the item can be easily observed by others, as is the case for outdoor products.

3.2.2 Pseudo-individual bid level analysis

The data collected from Bidster.com unfortunately do not allow for a detailed individual analysis, because it is not possible to retrieve participants' personal characteristics - e.g. gender, age, citizenship - or their specific bidding histories. Despite this limitation, it is still possible to construct a pseudo-individual bid level analysis with the available information. Specifically, by knowing the number of price observations (η), the retail price (p_{ret}), the bidding fee (c), and the size of the price decrease (Δ), one can easily reconstruct an item's current price at the moment of each price observation and relate this price with the agent's choice whether to buy the item or not. We can then estimate a model for the probability to buy the item (i.e., to end the auction). This approach is similar to the one implemented by Augenblick (2015) in the context of penny auctions. The reference equation is the following:

$$End_i = \beta_0 + \beta_1 CurrentPrice_i + \beta_2 c + \beta_3 Apple + \beta_4 Outdoor + \beta_5 Apple * Outdoor + \varepsilon_i \quad (7)$$

where End_i is a dummy variable taking value 1 if agent $i \in N$ decides to buy the item after he/she observes the current price ($CurrentPrice_i$). As before, c is the bidding fee, *Apple* is an indicator variable for Apple-branded products, and *Outdoor* is an indicator for products used outdoor. Coefficients from Probit estimations are reported in Table 4. Table 5 displays the correspondent marginal effects. Standard errors are clustered at the auction level to correct for possible error correlation within each auction.

Monetary variables present the expected signs and all the coefficients are extremely stable across all model specifications. In particular, the coefficient for the current price is negative and statistically significant. An increase in the observed price explains a significant reduction in the probability to buy the item. The coefficient for the bidding fee is instead positive. In line with the interpretation provided in Section 3.2.1, a large fee is paid only by highly interested agents, i.e., agents that are more likely to buy the item.

The bottom part of Tables 4 and 5 reports results concerning brand-driven and visibility-driven effects. Our aim is again to understand if the brand and the level of external visibility are important predictors of an individual's decision to buy the item. At first glance, the marginal effects for the three variables of interest - columns (3) to (5) in Table 5 - appear to be small in absolute value. However, considering that the baseline rate of an auction ending is approximately 0.02%, the estimated effects are actually relevant in magnitude. The results are consistent with the ones previously described in the auction level analysis. In particular, when considered in isolation, both the *Apple* and *Outdoor* variables explain an increase in the probability to buy the item, with an estimated marginal effect of 0.09%. The combined effect of these two variables generates a marginal effect of 0.12%. The relevance of the interaction term is confirmed - at least in terms of the magnitude of the coefficients - when all the three variables are jointly included (see Column 6). Indeed, and in line with the analysis at the auction level (which showed that the brand effect only matters insofar it is conveyed by an outdoor product), it is interesting that in the complete model the Apple effect dramatically drops, whereas the coefficient for the interaction term remains sizeable, although not statistically significant.

4 Sensitivity analysis

In this section, we implement a series of robustness checks. The sensitivity analysis addresses several specific features of the dataset as well as some of the assumptions of our empirical strategy. The first test that we perform consists of using an alternative dependent variable, namely the auction duration in hours. On the one hand, the stability of monetary effects on profits and on the number of price observations does not require further analysis. On the other hand, brand-driven and visibility-driven effects need additional evidence to validate previous results. The reason for introducing this new dependent variable is that, although auction timing and duration do not play any role in the PRA mechanism, duration is strongly correlated with the number of price observations. As such, the former can be used as a proxy for the latter.[10] Table 6 shows the estimation results. Monetary variables confirm the sign of their effects (positive for the retail price and negative for the bidding fee, although in the latter case the coefficient is not statistically significant). The results also display a strong and negative influence of the variable *Apple*. The variable *Outdoor* triggers an even larger effect. However, columns 5 and 6 confirm that it is the interaction of these two variables that substantially influences participants' behavior.

As a second robustness check, we address the existence of possible outliers. The potential impact of outliers is indeed a reason of concern due to the reduced sample size. In the main

[10] The correlation between number of price observations (η) and auction duration in hours (h) is 0.32 and is statistically significant at the 1% level.

analysis, we used the whole sample, as there were no reasons to exclude any observation *a priori*. Nonetheless, the descriptive analysis in Section 3.1 suggests the possible existence of outliers. We thus perform an influential data analysis aimed at understanding the effects of such outliers on the estimated coefficients. We compute Cook's distance (Cook, 1977, Cook, 1979) for each model of Tables 2 and 3. Two alternative thresholds are used to identify outliers. According to Cook and Weisberg (1982), each observation with a distance larger than 1 should be considered as influential. As shown in Table 7, there are no such observations in our sample. A more restrictive criterion is based on a threshold for Cook's distance equal to $4/(N-k-1)$ where N is the number of observations in the whole sample and k is the number of estimated parameters (e.g. Bollen and Jackman, 1990). Results for this restricted sample analysis are reported in Table 7. As far as profits are concerned (see the upper panel), the analysis confirms the results regarding the effects of the monetary variables and of the item's social attributes. In particular, the coefficients for the variables *Apple*, *Outdoor*, and *Apple*∗*Outdoor* remain negative and increasing in magnitude when each variable is considered in isolation. However, the coefficient for the interaction term appears to be the most relevant, both in terms of size and statistical significance. Results on the number of price observations (see the lower panel) are also consistent with those obtained in the main analysis. Monetary variables are stable across models and display the usual signs. *Apple* and *Outdoor* negatively affect the number of price observations, although it is the interaction of these two effects - see columns (5) and (6) - that emerges as the main determinant of the decrease in the number of price observations.

The last test we conduct concerns an auction's starting price. As already mentioned, we do not know the starting price of each item. In the main empirical analysis we assumed this to coincide with the retail price. This decision was driven by the fact that the seller chooses the starting price and is incentivized to choose a price as high as plausible; this is equivalent to saying that the seller sets $\alpha = 1$ (see the theoretical model in Section 2). In this test we relax this assumption. In particular, and in line with the initial example provided in the Introduction, we repeat the analysis under the assumption that $\alpha = 0.95$.[11] Table 8 reports the results. The upper panel (respectively, lower panel) of the table refers to the case in which the dependent variable is profits (respectively, number of price observations). The results are

[11] We replicated the analysis also with a value $\alpha = 90\%$ and still obtained similar results. These results are available upon request.

remarkably similar to the ones obtained in the main analysis (obviously, the coefficient for the effect of the retail price on profits is lower in magnitude; this effect is particularly strong for items with a higher market value). In addition, the usual pattern regarding brand and visibility effects emerges also in this framework.

5 Conclusions

We provided the first systematic empirical analysis of a recent online selling mechanism, the so-called price reveal auction (PRA). We studied the determinants of the mechanism's profitability and highlighted several important factors that influence consumers' behavior in online markets.

We feel that our results are useful in two dimensions. First, knowing which factors shape sellers' profits can help improve the design of the mechanism. This is valuable, as PRAs may find applications in other contexts such as charities or fund-raising activities. Indeed, the PRA format tickles participants' curiosity and can turn out to be particularly suitable in situations in which participants are more consciously willing to 'lose some money'. In this respect, our results are non-trivial, as we showed that a PRA is effective (i.e., raises higher profits) for selling items with good intrinsic qualities but no positional value. These are, in fact, items that consumers are willing to buy only at a substantial discount from the retail price. For such an item, the PRA attracts many price observations and thus promotes a large accrual of the associated bidding fees. Notice also that insights about the profitability of PRAs can be relevant in assessing the pros and the cons of similar formats that already exist (say, other pay-per-bid mechanisms) or that will appear in the future. In this respect, a sound knowledge of existing mechanisms is a key factor to guide regulation and implement effective policies for consumers' protection.

Second, our analysis conveys general results that pertain to consumers' behavior in online markets. Indeed, we highlighted how the social attributes of the item on sale, in particular the interaction of its brand with its level of external visibility, substantially affect participants' attitudes and willingness to pay. These results confirm the importance of an item's intangible aspects (brand recognition, status conferral, effects on the owner's self-image) in shaping buyers' behavior. These aspects must thus be given the highest consideration in choosing the appropriate selling mechanism to use, as well as the related pricing policies.

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Tables

Table 1: Descriptive statistics

Variables	Mean	St.Dev.	Median	Min.	Max.
Retail Price	442.77	374.30	320	25	1,700
Final Price	302.23	278.27	210.50	6	1,278
Bidding Fee	1.07	1.08	0.50	0.50	10
Price Decrease	0.53	0.54	0.25	0.25	5
Discount (%)	0.36	0.16	0.34	0.07	0.97
Duration (hours)	1,211	1,118	862	17	7,388
Number of price obs.	402.95	436.97	296	4	3,595
Profits	140.53	132.67	111.37	3.50	983
Apple	0.25	-	-	0	1
Outdoor	0.26	-	-	0	1
Apple & Outdoor	0.19	-	-	0	1
Observations			134		

All monetary values are expressed in €.

Table 2: The determinants of auctioneer's profit

Dependent variable: Profits						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	94.41***	93.96***	95.78***	98.69***	97.89***	98.73***
	(14.74)	(14.65)	(15.09)	(16.08)	(15.39)	(16.23)
log(Bidding Fee)		7.44	2.20	1.74	1.98	2.64
		(13.69)	(14.10)	(13.93)	(13.78)	(14.57)
Apple			-30.70*			17.48
			(18.51)			(13.57)
Outdoor				-40.29*		-12.53
				(21.37)		(24.60)
Apple & Outdoor					-47.75**	-52.60**
					(21.24)	(24.44)
N	134	134	134	134	134	134
R^2	0.45	0.46	0.47	0.47	0.47	0.48

Robust standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively.

Table 3: The determinants of the number of price observations

Dependent variable: Number of price observations						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	257.88***	274.80***	283.26***	296.48***	291.62***	296.30***
	(49.38)	(46.63)	(48.09)	(51.32)	(49.02)	(51.47)
log(Bidding Fee)		-278.36***	-302.78***	-304.49***	-301.73***	-303.35***
		(34.06)	(40.21)	(39.94)	(37.87)	(42.75)
Apple			-143.06**			32.32
			(65.91)			(53.86)
Outdoor				-184.82**		-93.63
				(73.18)		(84.75)
Apple & Outdoor					-204.32***	-150.95*
					(71.50)	(85.03)
N	134	134	134	134	134	134
R^2	0.31	0.51	0.53	0.54	0.54	0.54

Robust standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively.

Table 4: The determinants of auction's ending - Probit model estimations

Dependent variable: End auction						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Current Price)	-0.29***	-0.30***	-0.31***	-0.32***	-0.31***	-0.31***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
log(Bidding Fee)		0.33***	0.35***	0.35***	0.34***	0.35***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Apple			0.12***			0.03
			(0.04)			(0.07)
Outdoor				0.12***		0.05
				(0.04)		(0.03)
Apple & Outdoor					0.15***	0.08
					(0.05)	(0.09)
N	53,996	53,996	53,996	53,996	53,996	53,996
Pseudo-R^2	0.05	0.08	0.08	0.08	0.08	0.08

Probit regression models. Clustered at auction level standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively.

Table 5: The determinants of auction's ending

Dependent variable: End auction						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Current Price)	-0.0021***	-0.0022***	-0.0022***	-0.0023***	-0.0023***	-0.0023***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
log(Bidding Fee)		0.0024***	0.0025***	0.0025***	0.0025***	0.0025***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Apple			0.0009***			0.0002
			(0.0003)			(0.0005)
Outdoor				0.0009***		0.0003
				(0.0003)		(0.0002)
Apple & Outdoor					0.0011***	0.0006
					(0.0003)	(0.0006)
N	53,996	53,996	53,996	53,996	53,996	53,996
Pseudo-R^2	0.0555	0.0798	0.0814	0.0815	0.0819	0.0820

Table reports marginal effects for probit regression models. Clustered at auction level standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively.

Table 6: Sensitivity analysis: The determinants of auction's duration

Dependent variable: Duration in hours						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	194.74	200.89	240.96*	288.80**	292.34**	289.52**
	(126.91)	(127.13)	(130.37)	(125.73)	(121.64)	(127.84)
log(Bidding Fee)		-101.14	-216.83	-207.12	-228.21	-178.44
		(146.63)	(153.87)	(156.70)	(147.33)	(155.73)
Apple			-677.69***			584.20
			(230.35)			(476.19)
Outdoor				-749.39***		272.17
				(216.23)		(340.90)
Apple & Outdoor					-1110.85***	-1884.05***
					(173.79)	(565.27)
N	134	134	134	134	134	134
R^2	0.03	0.03	0.10	0.11	0.18	0.19

Robust standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively.

Table 7: Sensitivity analysis: Outliers

Dependent variable: Profits						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	71.18***	72.29***	76.48***	77.74***	79.75***	77.86***
	(5.69)	(6.11)	(6.76)	(7.03)	(6.80)	(7.14)
log(Bidding Fee)		11.28	7.28	7.19	6.48	8.96
		(6.89)	(7.58)	(7.66)	(7.50)	(7.92)
Apple			-12.04			28.50***
			(12.88)			(9.48)
Outdoor				-15.90		14.05
				(13.54)		(18.12)
Outdoor & Apple					-30.58**	-65.03***
					(15.32)	(22.29)
N	128	130	131	131	130	131
R^2	0.60	0.63	0.63	0.63	0.64	0.65
Influential Analysis - Cook's Distance:						
Min	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
Max	0.82	0.72	0.56	0.60	0.58	0.40
Dependent variable: Number of price observations						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	190.38***	204.68***	209.19***	216.19***	213.52***	214.13***
	(21.19)	(18.41)	(17.35)	(18.06)	(17.43)	(17.50)
log(Bidding Fee)		-235.56***	-245.85***	-248.20***	-247.19***	-239.32***
		(19.57)	(18.37)	(19.01)	(18.67)	(18.18)
Apple			-55.98			98.24
			(39.26)			(70.16)
Outdoor				-80.30**		-26.76
				(38.62)		(40.20)
Outdoor & Apple					-133.12***	-170.44*
					(40.57)	(89.34)
N	130	131	131	131	130	130
R^2	0.36	0.66	0.66	0.67	0.69	0.68
Influential Analysis - Cook's Distance:						
Min	~ 0	~ 0	~ 0	~ 0	~ 0	~ 0
Max	0.98	0.94	0.86	0.94	0.87	0.64

Robust standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively. Sample restricted by the exclusion of observations whose Cook's distance is higher than the ratio $4/(N-k-1)$.

Table 8: Sensitivity analysis: Starting Price ($\alpha = 0.95$)

Dependent variable: Profits						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	60.18***	59.69***	61.89***	64.11***	63.69***	63.89***
	(12.92)	(12.82)	(13.14)	(14.08)	(13.43)	(14.17)
log(Bidding Fee)		8.08	1.74	2.75	2.52	2.28
		(12.88)	(13.15)	(13.05)	(12.90)	(13.56)
Apple			-37.15**			-0.77
			(16.78)			(13.03)
Outdoor				-37.70*		-4.80
				(19.38)		(22.07)
Apple & Outdoor					-48.60**	-43.66*
					(19.53)	(23.26)
N	134	134	134	134	134	134
R^2	0.30	0.30	0.32	0.32	0.33	0.33

Dependent variable: Number of price observations						
	(1)	(2)	(3)	(4)	(5)	(6)
log(Retail Price)	207.53***	221.45***	230.34***	242.04***	238.06***	241.44***
	(44.49)	(42.87)	(44.08)	(47.16)	(44.94)	(47.24)
log(Bidding Fee)		-228.92***	-254.61***	-253.75***	-252.00***	-254.77***
		(31.00)	(36.53)	(36.34)	(34.34)	(39.01)
Apple			-150.48**			3.60
			(61.74)			(45.85)
Outdoor				-175.55**		-74.71
				(68.75)		(78.59)
Apple & Outdoor					-201.80***	-138.98*
					(67.97)	(78.49)
N	134	134	134	134	134	134
R^2	0.27	0.44	0.47	0.48	0.48	0.48

Robust standard errors are reported in brackets. *, **, *** denotes statistical significance at 10%, 5% and 1% level respectively. Profits and number of price observations are obtained under the assumption that the Starting Price is equal to 95% of the Retail Price.