Competing Trade Mechanisms and Monotone Mechanism Choice*

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Abstract

We investigate the choice between posted prices and auctions of competing sellers with private valuations. Assuming that buyers face higher hassle costs in auctions, we show the existence of monotone pure strategy equilibria where sellers offer posted prices rather than auctions if and only if they have a sufficiently high reservation value. Posted prices sell with lower probability but yield a larger revenue in case of trade. Using an empirical strategy to compare revenues of posted prices and auctions that takes selling probabilities explicitly into account, we find our theoretical predictions supported by data from eBay auctions on ticket sales for the EURO 2008 European Football Championship.

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1 Introduction

Anyone who wishes to sell via an (online) trading platform has to decide upon two issues: What *type* of trade mechanism to choose and how to *specify* this mechanism. At eBay,

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for instance, sellers can decide to run an auction or to offer a transaction at a posted price and have to fix a reserve price for the auction or the posted price.[1] A first glance at actual eBay transactions typically hints at a trade-off: Auctions are more likely to be successful but yield a lower average revenue than posted-price transactions.[2] This seems to be in contrast to the textbook advice that auctions are better for sellers than posted-price offers because they permit sellers to price discriminate with respect to bidders' valuations.

Recently, Einav et al. (2018) suggested an explanation for this empirical observation: If a seller has high opportunity costs of selling the item and, therefore, wants to sell it only if the price is sufficiently high, it is unlikely that there are at least two bidders with valuations above that price participating at the mechanism. However, this would be exactly the scenario in which an auction outperforms a uniform posted price. If, in addition, buyers incur hassle costs when participating at an auction, a monopolistic seller may strictly prefer offering the item at a posted price rather than at an auction.[3] As a result, posted prices tend to be high and sell with a low probability, whereas auctions tend to have low reserve prices and be sold with high probability but at a low expected revenue conditional on sale.

In this paper, we extend this analysis of selling probabilities and expected revenue conditional on sale to the question of competing sellers' equilibrium choices of mechanism, and present empirical evidence in support of the model's main predictions. Theoretically we find that, if buyers and sellers only care about the probability and the price of a transaction, posted prices will never be offered in equilibrium. By contrast, auction-specific hassle costs for buyers lead to a monotone pure strategy equilibrium where auctions and posted prices co-exist with positive probability. Consistent with Einav et al. (2018), posted prices (auctions) in such an equilibrium are chosen by sellers whose optimal mechanism has a low (high) selling probability.

[1] In practice, there are several variants of posted price or auction-institutions (e.g. at eBay it is possible to allow for price suggestions by buyers or to set secret reserve prices in auctions) and hybrid designs such as buy-it-now options.

[2] See, for instance, Halcoussis and Mathews (2007) or Hammond (2010).

[3] Other advantages of posted prices have been established by Harris and Raviv (1981) (excess capacity), Wang (1993) (homogenous buyer valuations), Mathews (2004) (risk aversion) and Zeithammer and Liu (2006) (time discounting). Empirically, however, Ariely and Simonson (2003) and Malmendier and Lee (2011) find that auction prices frequently exceed simultaneous posted prices within or outside the auction platform, which the latter authors attribute to limited attention to posted prices by those who participate in auctions. In our dataset, 15.2% of auction prices are above at least one posted-price offer that was active at the same time.

We model the strategic choice between posted prices and auctions by a set of sellers as a finite action game with incomplete information as analyzed in Athey (2001). Sellers have quasi-linear preferences with a private valuation for one unit of a homogenous good drawn independently from (not necessarily identical) continuous probability distributions with full support. Each seller is endowed with one unit of the homogenous good and chooses between posted prices and auctions with start prices. For a given profile of chosen mechanisms, a seller offering a posted price sells at the posted price if and only if the posted price is below a market clearing price and a seller offering an auction sells at the market clearing price if and only if the start price is below the market clearing price. Market clearing prices are determined as in a sellers' offer double auction. Peters and Severinov (2006) demonstrated that such market clearing prices are equilibrium prices in a model of competing sellers offering auctions to cross-bidding buyers.

For a given strategy by the other sellers, any mechanism can be fully characterized by the induced probability of trade p and the expected revenue in case of trade R. The set of mechanisms at a seller's disposal (for given strategies of the other sellers) can therefore be depicted by a set of points in the plane, and we will refer to this set of points as a (p, R)–plot of mechanisms. For a given strategy of other sellers, a seller will never choose a mechanism that is dominated in the sense that another mechanism would either yield a higher selling probability with at least the same revenue in case of trade or a larger revenue with at least the same selling probability.

We first demonstrate that, without auction-specific hassle costs, a posted price f is always dominated by an auction with start price f and, as also shown with models of competitive mechanism design by McAfee (1993) or Peters (1997), sellers will only offer auctions with start prices that are monotone increasing in their valuation.[4] Part of the literature, however, has reasonably emphasized that posted prices may be preferred by at least some buyers due to lower hassle costs, impatience or risk aversion (see e.g. Bauner (2015)). We restrict attention to hassle costs that are higher for auctions. We then find that (p, R)–plots, and thereby equilibrium mechanism choices, exhibit single-crossing in the sense that sellers offer posted prices if and only if they have a sufficiently high valuation.

Our model yields a set of hypotheses regarding the shape and relative position of

[4] Eeckhout and Kircher (2010) demonstrate that the superiority of auctions over posted prices crucially depends on the search technology. Auctions - or other screening mechanisms - loose their superiority as compared to posted prices if a meeting between a seller and a buyer is sufficiently rival. Then, posted prices resemble an efficient device for an ex-ante sorting (rather than an ex-post screening) of buyers.

(p, R)–plots for posted prices and auctions. First of all, undominated mechanisms resemble a downward sloping graph in the (p, R)–plot as an undominated mechanism with lower selling probability yields a higher revenue in case of trade. Together with the single-crossing of undominated mechanisms in (p, R)–plots for posted prices and auctions, this permits us to compare aggregate performance of posted prices and auctions: Selling probabilities for posted prices are, in equilibrium, lower than selling probabilities for auctions, but successfully posted prices are above final auction prices. Moreover, we can characterize equilibrium mechanism choices of individual sellers: Single-crossing of (p, R)–plots of posted prices and auctions implies that there is an excess revenue of auctions relative to posted prices for large selling probabilities, but an excess revenue of posted prices over auctions for small selling probabilities. Hence, a seller's equilibrium mechanism choice is monotone in her valuation along the set of undominated mechanisms. She will choose an auction with a low start price (a high posted price) if her valuation is low (high).

In order to test the hypotheses derived from our model, we use data for tickets to matches of the 2008 UEFA European Football Championship, because the perishable nature and the lack of a competitive fringe guarantee sufficient heterogeneity in buyers' and sellers' valuations, and therefore in equilibrium mechanism choices. We provide support for the aforementioned insights on aggregate performances of posted prices and auctions by simple regression analysis. Furthermore, our data suggest that posted prices are sold with a higher probability than auctions with the same start price, which supports the assumption of bidders' auction-specific hassle cost. To test the main hypothesis from our model that auctions yield lower expected final prices conditional on sale than posted prices for sufficiently small identical selling probabilities, we first estimate the selling probability both for auctions and posted prices. We then use this predicted selling probability in order to explain the excess revenue of an auction over a hypothetical posted price at which this item would have needed to be offered in order to be sold with the same probability. In line with our model, we then find that auctions outperform posted prices for large identical selling probabilities and vice versa.

Our analysis regarding the existence of a monotone pure strategy equilibrium adds to the literature on competing mechanism designers that establishes the optimality of auctions and addresses the convergence of optimal start prices to the sellers' costs in a competitive equilibrium setting (see McAfee (1993) or Peters (1997)) or for competing auctions (see Peters and Severinov (1997), Burguet and Sakovics (1999), Peters and Severinov (2006), Hernando-Veciana (2005), or Virag (2010)). As this literature focuses on the emergence of efficient trade institutions as the result of competition between sellers, it is typically assumed that sellers have identical or publicly observable costs (for an exception see Peters (1997)). By contrast, our paper analyzes the impact of unobservable seller heterogeneity on mechanism choice and thereby addresses the question of optimal mechanism design for different types of sellers. Specifically, the representation of a seller's choice set by (p, R)–plots visualizes how straightforward trade-offs between selling probability and revenue in case of trade ensure the existence of pure strategy equilibria.[5]

Some of our empirical results are in line with previous empirical work on the comparison between auctions and posted prices: The aforementioned papers by Halcoussis and Mathews (2007), Hammond (2010) and Einav et al. (2013) also find that auctions are unconditionally more likely to be successful but yield a lower price conditional on sale than posted prices. Our theoretical model gives an explanation for this finding in the context of a platform with competing sellers by showing that, in equilibrium, auctions (posted prices) are typically chosen in combination with a low start price (high posted price), which implies a high (low) selling probability and low (high) expected revenue conditional on sale. In a dataset that includes almost all kinds of items sold on eBay, Einav et al. (2018) use variation in the same sellers' mechanism choices to empirically estimate single (p, R) – plots. We develop (p, R) – plots by exploiting heterogeneity of different sellers in a sample of homogenous items, controlling for observable item characteristics. In a different vein, Hammond (2013) and Bauner (2015) estimate a structural model of sellers' mechanism choices in order to make predictions about counterfactual markets. In their data, posted prices and auctions also co-exist, and sellers for whom they estimate higher valuations are more likely to choose posted prices. In contrast to all studies reviewed in this paragraph, we theoretically demonstrate the co-existence of auctions and posted prices in equilibrium, and apply an estimation strategy that is designed to test our theoretical hypotheses regarding (p, R)–plots.

The remainder of the paper is organized as follows: We will develop and analyze our theoretical model of mechanism choice by competing sellers and derive empirically testable hypotheses in Section 2. Section 3 presents our empirical analysis. We conclude in Section 4.

[5]The crucial role of this revenue-probability trade-off for equilibrium existence has been emphasized in the literature on competitive search where sellers who offer a smaller share of the surplus (and thereby keep a larger revenue for themselves) are visited less frequently by buyers; see, e.g., Moen (1997) or, more recently, Guerrieri et al. (2010) and Chang (2014).

2 Theory

2.1 The Model

Consider the following set-up modelling online trade. $s \geq 2$ risk-neutral sellers are endowed with one unit of an indivisible, homogenous good. Seller $i \in \mathcal{S} \equiv \{1, ..., s\}$ has reservation value $r_i \in [0, 1]$ for her unit of the good. For each $i \in \mathcal{S}$, r_i is distributed with continuous density $h_i(r_i)$ with full support on $[0, 1]$.

$b > s$ risk-neutral buyers like to purchase one unit of the indivisible, homogenous good. Buyer $j \in \mathcal{B} \equiv \{1, ..., b\}$ has valuation $v_j \in [0, 1]$ for one unit of the good. For each $j \in \mathcal{B}$, v_j is distributed with continuous density $g_j(v_j)$ with full support on $[0, 1]$. I.e., sellers and buyers have independently drawn private valuations for one unit of the indivisible good.[6] We will refer to the vector $\mathbf{r} = (r_1, ..., r_s)$ as the sellers' and to the vector $\mathbf{v} = (v_1, ..., v_b)$ as the buyers' *profile*, and we call the collection $(\mathcal{B}, \mathcal{S})$ a *market*.

The set $\mathcal{M}_i$ of mechanisms at seller i's disposal consists of posted price offers f_i and English auctions with start price s_i where $f_i, s_i \in \mathcal{P}$ with $\mathcal{P} = \{0, \delta, 2\delta, \ldots, 1\}$ being a grid with grid step $\delta \leq \frac{1}{2}$.[7] If buyer j fails to trade, his utility is zero. As auctions take some time and yield an (ex-ante) uncertain payoff, we allow buyers to have higher hassle costs when trading at an auction rather than a posted price, and we denote this difference in hassle costs by $c \in [0, 1)$. That is to say, a buyer j with valuation v_j strictly prefers an auction with final price p to a posted price transaction at final price f if and only if $v_j - p - c > v_j - f$.

First, all sellers simultaneously choose a mechanism and then buyers compete for the offered units. Denote the sellers' choices of mechanisms as a profile $\mathbf{m} = (m_1, \ldots, m_s) \in \mathcal{M}_1 \times \ldots \mathcal{M}_s$ with m_i being the mechanism (i.e., the posted price f_i or the start price s_i) chosen by seller i.

[6]Assuming that the number of buyers exceeds the number of sellers is the relevant case in our dataset; see Section 3.1. For the model, it implies that any posted price or start price of seller i has a strictly positive probability to become the market clearing price. Whenever there are more sellers than buyers, it depends on the (expected) profile of mechanisms offered by other sellers whether seller i's posted price or start price can be the market clearing price.

[7]We assume a regular grid to ease the exposition. The results remain valid for any finite set of at least three prices including 0 and 1.

2.2 Buyer competition

For a given profile $\mathbf{m}$ of sellers' mechanism choices, we assume perfect competition among buyers, i.e., sellers and buyers trade at market-clearing prices. To be specific, consider a profile of mechanisms $\mathbf{m}$ and a profile of valuations $\mathbf{v}$. Denote by $\mathbf{m}_c$ the profile of mechanisms accounting for buyers' preference for an auction if and only if $v_j - p - c > v_j - f$, i.e., $m_i = f_i - c$ if seller i offers posted price f_i and $m_i = s_i$ if seller i offers an auction with start price s_i. The market clearing price $p^*(\mathbf{m}, \mathbf{v})$ is the $|\mathcal{B}|$th lowest value in $(\mathbf{m}_c, \mathbf{v})$, i.e., we assume that market clearing prices are determined as in a sellers' offer double auction.[8] Seller i who offered posted price f_i trades if and only if $f_i - c \leq p^*$ and receives a payoff of $f_i - r_i$. Seller i who offered an auction with start price s_i trades if and only if $s_i \leq p^*$ and receives a payoff of $p^* - r_i$. Buyer j trades if and only if $v_j > p^*$ and receives a payoff of $v_j - p^*$ if he traded at an auction and a payoff of $v_j - f_i + c$ if he traded at posted price f_i.[9]

2.3 Seller's mechanism choice

(p, R)**–plots** When sellers simultaneously choose mechanisms, each seller i picks a mechanism from $\mathcal{M}_i$ that maximizes her expected revenue given the distribution of expected mechanism choices by the other sellers and subsequent buyer competition as described in the previous paragraph. To fix notation, let seller i expect seller j to choose a mechanism according to the probability distribution $\mu_{ij} : \mathcal{M}_j \to [0, 1]$, and denote the corresponding profile of probability distributions by $\mu_i = (\mu_{ij})_{j \neq i}$. For a given profile μ_i, each mechanism $m_i \in \mathcal{M}_i$ yields a selling probability $p(\mu_i, m_i)$ and an expected revenue conditional on selling $R(\mu_i, m_i)$. For further reference, denote seller i's expected utility from mechanism m_i given expectations μ_i and reservation value r_i by $U_i(\mu_i, m_i, r_i)$.

We will refer to a plot that, for a given seller i for each mechanism $m_i \in \mathcal{M}_i$ and expectations μ_i, depicts the revenue conditional on selling $R(\mu_i, m_i)$ on the vertical and

[8] Results do not rely on this particular rule of determining market clearing prices and hold for any k-double auction.

[9] Technically, we assume that buyers benefit from trading at a posted price rather than suffer from trading at an auction. Alternatively, one could assume that buyer valuations include auction specific hassle costs and posted prices induce hassle costs that are lower by c. All that matters is the difference in hassle costs in favor of posted prices. Simply assuming (uniform) hassle costs in auctions would require considering different supports of valuations for buyers and sellers (or sufficiently high buyer/seller ratios) to accommodate the empirical finding that auctions with a start price of zero (almost) always sell the item.

the selling probability $p(\mu_i, m_i)$ on the horizontal axis as a (p, R)–plot. As expected market clearing prices conditional on being above f_i (or s_i) are increasing in f_i (or s_i), (p, R)–plots for auctions and posted prices are downward-sloping.

Lemma 1 *(i) Consider seller i with expectations μ_i and two auctions with start prices s_i and s_i' and $s_i' > s_i$. Then, $p(\mu_i, s_i) > p(\mu_i, s_i')$ and $R(\mu_i, s_i) < R(\mu_i, s_i')$. (ii) Consider two posted prices $f_i' > f_i$. Then, $p(\mu_i, f_i) > p(\mu_i, f_i')$ and $R(\mu_i, f_i) < R(\mu_i, f_i')$.*

Proof. Let m_i be a mechanism offered by seller i with reservation value r_i and expectations μ_i. Then, $p(\mu_i, m_i)$ depicts the probability that the market clearing price at least s_i if m_i is an auction with start price s_i or at least f_i if m_i is a posted price offer at f_i. For a profile of mechanisms and valuations $(\mathbf{m}, \mathbf{v})$, the market clearing price is the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$. Whenever the $|\mathcal{B}|$th lowest value is at least s_i' (f_i'), it is also at least $s_i < s_i'$ $(f_i < f_i')$. This implies $p(\mu_i, s_i) \geq p(\mu_i, s_i')$ $(p(\mu_i, f_i) \geq p(\mu_i, f_i'))$. Since there are more buyers than sellers $(b > s)$ and $\mathbf{v}$ has full support, there is a positive probability that the market clearing price is in (s_i, s_i') $((f_i, f_i'))$. This implies $p(\mu_i, s_i) > p(\mu_i, s_i')$ $(p(\mu_i, f_i) > p(\mu_i, f_i'))$. Moreover, the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$ conditional on being above s_i' (f_i') weakly exceeds the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$ conditional on being above $s_i < s_i'$ $(f_i < f_i')$ in any profile $(\mathbf{m_c}, \mathbf{v})$. Together with the full support of $\mathbf{v}$ that induces a positive probability of s_i (f_i) to be a market clearing price and implies $R(\mu_i, s_i) < R(\mu_i, s_i')$ $(R(\mu_i, f_i) < R(\mu_i, f_i'))$. ■

A particular feature of buyer competition in our model is that all auctions trade at a (uniform) market clearing price. This implies that the expected final price conditional on selling at an auction with start price s_i (i.e., the expected market clearing price conditional on being weakly larger than s_i) is increasing in s_i (see Lemma 1(i)). Expected prices unconditional on sale, however, are independent of s_i.

Lemma 2 *Consider two auctions with start prices s_i and s_i' with $s_i' > s_i$, and suppose both auctions sell the item. Then, final auction prices are identical.*

With hassle costs for auctions (i.e., $c > 0$), the item is sold at a posted price f if and only if $f - c \leq p^*$ and the item is sold at an auction with start price s if and only if $s \leq p^*$. Hence, the item is more likely to be sold at a posted price f than at an auction with start price $s = f$.

Lemma 3 *Consider seller i with expectations μ_i and a mechanism m_i that offers trade at a posted price f_i and a mechanism m_i' that offers trade at an auction with start price*

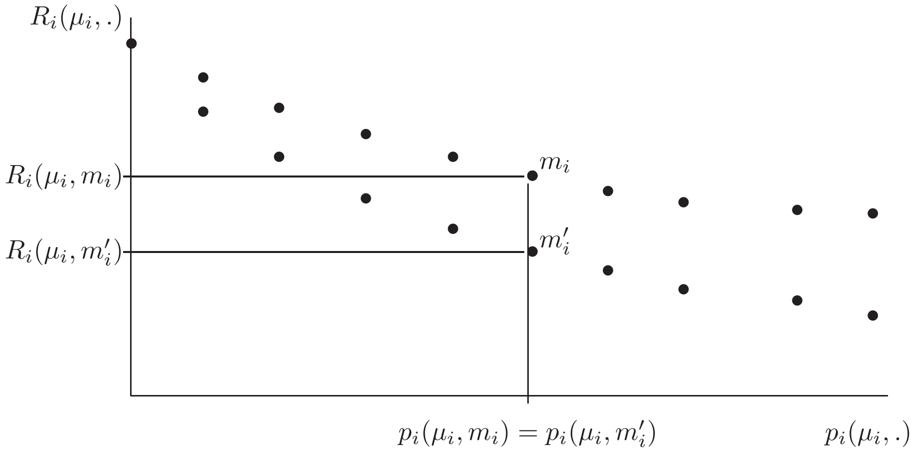

Figure 1: An example of (p, R)–plots for auctions and posted prices without hassle costs.

$s_i = f_i$. *(i) Suppose* $c = 0$. *Then,* $p(\mu_i, m_i) = p(\mu_i, m_i')$. *(ii) Suppose* $c > 0$. *Then,* $p(\mu_i, m_i) > p(\mu_i, m_i')$.

Proof. Let m_i be a mechanism offered by seller i with reservation value r_i and expectations μ_i. Then, $p(\mu_i, m_i)$ depicts the probability that the market clearing price is at least s_i if m_i is an auction with start price s_i or at least $f_i - c$ if m_i is a posted price offer at f_i. For a profile of mechanisms and valuations $(\mathbf{m}, \mathbf{v})$, the market clearing price is the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$. For $c = 0$, the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$ is the same for an auction with start price s_i and a posted offer at a fixed price $f_i = s_i$. This implies $p(\mu_i, s_i) = p(\mu_i, f_i)$. For $c > 0$, the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$ if i offers a fixed price f_i is at most as large as the $|\mathcal{B}|$th lowest value if i offers an auction with $s_i = f_i$. This implies $p(\mu_i, f_i) \geq p(\mu_i, s_i)$. Since there are more buyers than sellers ($b > s$) and $\mathbf{v}$ has full support, there is a positive probability that $f_i - c < s_i$ is the market clearing price. This implies $p(\mu_i, f_i) > p(\mu_i, s_i)$. ■

2.4 No hassle costs

For $c = 0$, it is straightforward to see that the item is sold at a posted price f with the same probability as at an auction with start price f (see Lemma 3). In both cases, the selling probability is the probability that the market clearing price is at least f. Auctions, however, yield a revenue conditional on sale that is strictly larger than f (unless $f = 1$) as all prices between 0 and 1 can be market clearing prices given the full support assumption on the distribution of buyers' profiles. As a consequence, an auction m_i with start price $s = f$ is to the north of a mechanism m_i' with posted price f in the (p, R)–plot of seller i (see Figure 1) and sellers will never choose to sell at a posted price.

Lemma 4 *Suppose $c = 0$ and consider seller i with expectations μ_i and a mechanism m_i that offers trade at a posted price f_i and a mechanism m'_i that offers trade at an auction with start price $s_i = f_i$. Then, $R(\mu_i, m_i) < (=) R(\mu_i, m'_i)$ and $U_i(\mu_i, m_i, r_i) < (=) U_i(\mu_i, m'_i, r_i)$ for $f < 1$ (for $f = 1$).*

Proof. Let m_i and m'_i be mechanisms offered by seller i with reservation value r_i and expectations μ_i and suppose m_i is an auction with start price s_i and m'_i is a posted price $f_i = s_i$. Then, $R(\mu_i, m_i)$ is the expected market clearing price conditional on the market clearing price being at least s_i and $R(\mu_i, m'_i) = s_i$. For a profile of mechanisms and valuations $(\mathbf{m}, \mathbf{v})$, the market clearing price is the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$. For $c = 0$, the $|\mathcal{B}|$th lowest value in $(\mathbf{m_c}, \mathbf{v})$ is the same for an auction with start price s_i and a posted offer at a fixed price $f_i = s_i$. This implies $p(\mu_i, m_i) = p(\mu_i, m'_i)$. Since there are more buyers than sellers ($b > s$) and $\mathbf{v}$ has full support, there is a positive probability that the market clearing price strictly exceeds s_i. This implies $R(\mu_i, m_i) > R(\mu_i, m'_i)$ for $f < 1$ (see Figure 1) and $R(\mu_i, m_i) = R(\mu_i, m'_i)$ for $f = 1$. Together with $p(\mu_i, m_i) = p(\mu_i, m'_i)$, this implies $U_i(\mu_i, m_i, r_i) < (=) U_i(\mu_i, m'_i, r_i)$ for $f < 1$ (for $f = 1$). ■

As higher start prices yield strictly lower selling probabilities and strictly larger revenues conditional on sale, there is single-crossing with respect to start price choices.

Lemma 5 *Suppose $c = 0$ and consider seller i with expectations μ_i and reservation value r_i. Let $s'_i > s_i$ and suppose that $U_i(\mu_i, s'_i, r_i) \geq U_i(\mu_i, s_i, r_i)$. Then, $U_i(\mu_i, s'_i, r'_i) > U_i(\mu_i, s_i, r'_i)$ for all $r'_i > r_i$.*

Proof. Suppose $c = 0$ and consider seller i with expectations μ_i and reservation value r_i offering an auction with start price s_i or an auction with start price $s'_i > s_i$ and suppose that $U_i(\mu_i, s'_i, r_i) \geq U_i(\mu_i, s_i, r_i)$. Then, for $r'_i > r_i$,

$$\begin{aligned}
U_i(\mu_i, s'_i, r'_i) &= p(\mu_i, s'_i) R(\mu_i, s'_i) + (1 - p(\mu_i, s'_i)) r'_i \\
&= p(\mu_i, s'_i) R(\mu_i, s'_i) + (1 - p(\mu_i, s'_i)) r_i + (1 - p(\mu_i, s'_i))(r'_i - r_i) \\
&= U_i(\mu_i, s'_i, r_i) + (1 - p(\mu_i, s'_i))(r'_i - r_i) \\
&\geq U_i(\mu_i, s_i, r_i) + (1 - p(\mu_i, s'_i))(r'_i - r_i) \\
&> U_i(\mu_i, s_i, r_i) + (1 - p(\mu_i, s_i))(r'_i - r_i) = U_i(\mu_i, s_i, r'_i)
\end{aligned}$$

where the first inequality follows from $U_i(\mu_i, s'_i, r_i) \geq U_i(\mu_i, s_i, r_i)$ and the second from $p(\mu_i, s_i) > p(\mu_i, s'_i)$ (see Lemma 1). ■

This single-crossing result together with Theorem 1 in Athey (2001) implies that there exists a monotone pure strategy equilibrium in which sellers with higher reservation values choose auctions with higher start prices.

Proposition 1 *Suppose $c = 0$. Then, there is a pure strategy equilibrium in which all sellers offer auctions and s_i is monotone increasing in r_i.*

Proof. Suppose $c = 0$. By Lemma 4, a posted price f is (weakly) dominated by an auction with start price $s = f$. Hence, we can restrict ourselves to mechanisms being auctions with start prices in $\mathcal{P}$. By Lemma 5, the single-crossing condition for games of incomplete information (SCC) in Definition 3 of Athey (2001) is satisfied for a seller's strategy being the choice of a start price. As we assume private values for buyers and sellers, also Assumption 1 in Athey (2001) is satisfied. Then, Theorem 1 in Athey (2001) implies the existence of a pure strategy equilibrium in non-decreasing strategies, i.e., with seller's choosing (weakly) higher start prices as their reservation value increases. ■

2.5 Auction specific hassle costs

For $c > 0$, the (p, R)–plot of auctions is no longer (weakly) to the north of the (p, R)–plot of posted prices but single-crosses the (p, R)–plot of posted prices from below. To see this, observe first that the item is sold at a mechanism m_i offered by seller i at a posted price of 1 with a strictly larger probability than with an auction $\bar{m}_i$ with start price 1 (while the revenue conditional on sale remains the same). Hence, the (p, R)–plot of posted prices starts to the right of the (p, R)–plot of auctions (see Figure 2). On the other hand, there is a single-crossing result for (p, R)–plots of the following kind: If an auction $\bar{m}_i$ with start price s yields – for given beliefs of the seller – a larger revenue in case of sale than a mechanism m_i with a posted price that is sold with the same probability (which is the posted price $f = s + c$), this also holds for any auction $\bar{m}'_i$ with a start price $s' < s$ and a mechanism m'_i with a posted price $f' = s' + c$ (see Figure 2).

Lemma 6 *Suppose $c > 0$ and consider seller i with expectations μ_i. (i) If m_i offers trade at a posted price f_i with $f_i = 1$ and $\bar{m}_i$ is an auction with start price $s_i = f_i$, then $p(\mu_i, m_i) > p(\mu_i, \bar{m}_i)$ and $R(\mu_i, m_i) = R(\mu_i, \bar{m}_i)$. (ii) If m_i offers trade at a posted price $f_i \geq c$ and $\bar{m}_i$ is an auction with start price $s_i = f_i - c$, then $p(\mu_i, m_i) = p(\mu_i, \bar{m}_i)$. Moreover, $R(\mu_i, m_i) < R(\mu_i, \bar{m}_i)$ implies $R(\mu_i, m'_i) < R(\mu_i, \bar{m}'_i)$ for all m'_i that offer trade at a posted price $c < f'_i < f_i$ and $\bar{m}'_i$ that offer trade at an auction with start price $f'_i - c$. (iii) Posted prices $f'_i < c$ are dominated by $f_i = c$.*

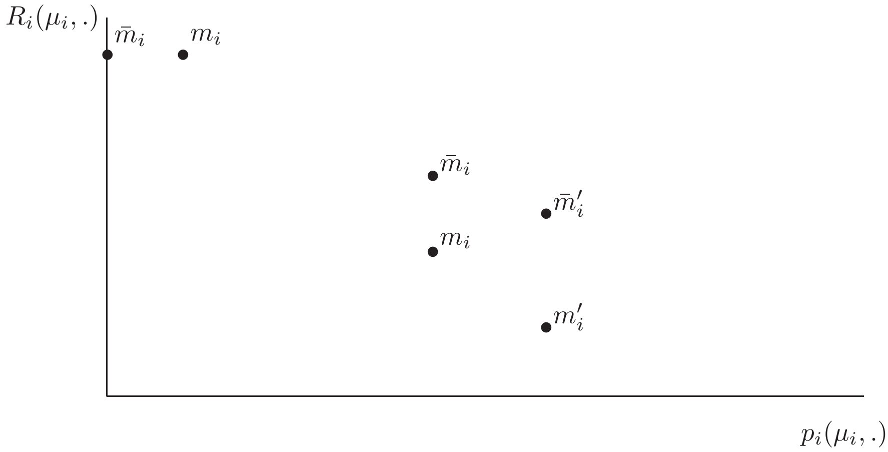

Figure 2: Elements of (p, R)–plots for auctions and posted prices with hassle costs.

Reducing the posted price by δ reduces revenue conditional on sale by δ, but reducing the start price of an auction by δ reduces revenue conditional on sale (by δ) only if the start price happens to be the market clearing price (which occurs with a probability strictly smaller than 1). Graphically, this implies a smaller negative slope of the (p, R)–plot of auctions and a single-crossing of (p, R)–plots for auctions and posted prices.

Proof. Let m_i and $\bar{m}_i$ be mechanisms offered by seller i with reservation value r_i and expectations μ_i. (i) Let m_i be a posted price $f_i = 1$ and $\bar{m}_i$ be an auction with start price $s_i = 1$. Obviously, $R(\mu_i, m_i) = R(\mu_i, \bar{m}_i)$. $p(\mu_i, m_i)$ is the probability that the market clearing price is (at least) $1 - c$ and $p(\mu_i, \bar{m}_i)$ is the probability that the market clearing price is at least 1. As $b > s$ and $\mathbf{v}$ has full support, this implies $p(\mu_i, \bar{m}_i) < p(\mu_i, m_i)$ (see Figure 2). (ii) Let m_i be a posted price $f_i \geq c$ and $\bar{m}_i$ be an auction with start price $s_i = f_i - c$. $p(\mu_i, m_i)$ is the probability that the market clearing price is at least $f_i - c$ and $p(\mu_i, \bar{m}_i)$ is the probability that the market clearing price is at least $s_i = f_i - c$. Hence, $p(\mu_i, \bar{m}_i) = p(\mu_i, m_i)$. Now suppose that $R(\mu_i, m_i) < R(\mu_i, \bar{m}_i)$, i.e., the auction with $s_i = f_i - c$ yields a larger revenue in case of sale than the posted price $f_i - c$ (which yields a revenue f_i in case of sale). As the revenue of a posted price conditional on sale is the posted price, $R(\mu_i, m'_i) = R(\mu_i, m_i) - \delta$ for a posted price offer m'_i at $f'_i = f_i - \delta$. By contrast, $R(\mu_i, \bar{m}'_i) > R(\mu_i, \bar{m}_i) - \delta$ for an auction $\bar{m}'_i$ with start price $s'_i = s_i - \delta$, as the market clearing price decreases by δ if and only if the start price s_i is the market clearing price. Given that $\mathbf{v}$ has full support, this is the case with a positive probability that is bounded away from 1. As this is true for all f_i, it follows that $R(\mu_i, m_i)$ with m_i being a posted price offer at f_i decreases more steeply in f_i than $R(\mu_i, \bar{m}_i)$ with $\bar{m}_i$ being an auction with start price $s_i = f_i - c$ while $p(\mu_i, m_i) = p(\mu_i, \bar{m}_i)$ for all $f_i \geq c$ (see Figure 2). (iii) As $b > s$, a posted price $f_i = c$ is sold with probability 1 for any profile of mechanisms $\mathbf{m_{-i}}$ offered by other sellers. A posted price $f_i' < c$ would, therefore, only reduce revenue in case of sale without being able to increase the selling probability. ■

As in the case without hassle costs, sellers with larger reservation value care less about the selling probability and more about the revenue conditional on sale, and therefore "move up the (p, R)–plot" as their reservation value increases. Hence, there is again a monotone pure strategy equilibrium where sellers with higher reservation values choose mechanisms with lower selling probability and larger revenue conditional on sale. The only difference is that these mechanisms are auctions for sufficiently small start prices and posted prices for sufficiently high reservation values.

Proposition 2 *Suppose $c > 0$. Then, there is a pure strategy equilibrium in which each seller i's equilibrium strategy exhibits a threshold valuation $\widetilde{r}_i \in [0, 1)$ such that i offers an auction if $r_i < \widetilde{r}_i$ and offers a posted price if $r_i \geq \widetilde{r}_i$.*

Proof. For seller i, consider the following ordering of strategies on $\mathcal{M}_i$: First, list all auctions with start prices from $s_i = 0$ to $s_i = 1$, then, add all posted prices from $f_i = 0$ to $f_i = 1$. Let $o(m_i)$ be the rank of mechanism m_i on this list. A monotone pure strategy of seller i is a strategy, $\alpha_i : [0, 1] \to \mathcal{M}_i$ such that for given beliefs $o(\alpha_i(r_i)) \geq o(\alpha_i(r_i'))$ for $r_i' > r_i$, i.e., seller i chooses mechanisms with higher start prices / posted prices and switches at most once from auctions to posted prices as her valuation increases. By Lemma 6, (p, R)–plots of auctions and posted prices for given beliefs cross at most once and posted prices are sold with a larger probability if the revenue in case of sale is sufficiently large. For given beliefs μ_i of seller i, consider two mechanisms m_i and m_i' with $p(\mu_i, m_i) > p(\mu_i, m_i')$. If $R(\mu_i, m_i) \geq R(\mu_i, m_i')$, m_i' will never be chosen by the seller. If $R(\mu_i, m_i) < R(\mu_i, m_i')$ and m_i' yields higher expected utility than m_i when the seller has reservation value r_i it also yields higher expected utility for any $r_i' > r_i$ because $p(\mu_i, m_i) > p(\mu_i, m_i')$ and the probability to enjoy the reservation value is larger under m_i'. This establishes single-crossing of mechanism choices as in Lemma 6 but now for the entire ordered list of mechanisms. Then, Theorem 1 in Athey (2001) implies the existence of a pure strategy equilibrium in non-decreasing strategies, i.e., with sellers' choosing mechanisms with a higher rank as their reservation value increases. ■

2.6 Testable Hypotheses

Our model yields the following set of testable hypotheses. First, our assumptions on buyer competition immediately imply that the lower the start price or posted price, the higher

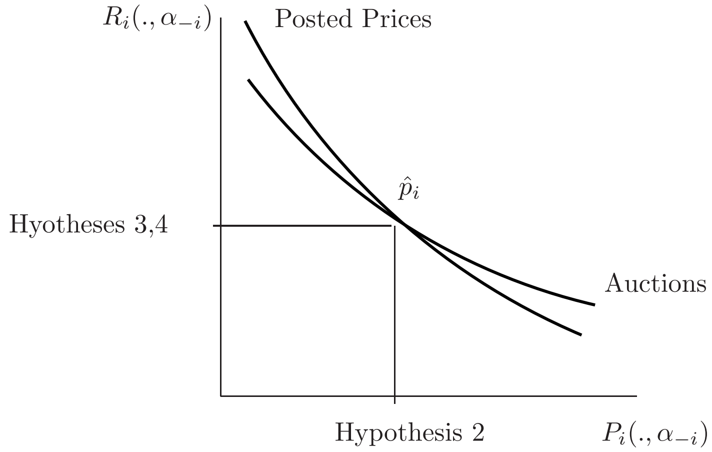

Figure 3: Single-crossing (p, R)–plot and Hypotheses 2–4.

the probability that the expected market clearing price is above the start price or posted price:

Hypothesis 1 *The selling probability of a particular item is decreasing in start prices and posted prices.*

For final auction prices, we need to take into account that observed prices are left censored to start prices (because expected market clearing prices are increasing in start prices). Thus, without correcting for censoring, auction prices are increasing in start prices (see Hypothesis 2a). Due to market-clearing, however, final auction prices should be independent of start prices when the corresponding regression corrects for censoring (see Hypothesis 2b).

Hypothesis 2 *a) Final auction prices increase in start prices. b) Final auction prices unconditional on sale are independent of start prices.*

While Hypothesis 1 mainly describes the usual trade-off between selling probability and selling price found in the empirical literature, the single-crossing of (p, R)–plots as established by Lemma 6 also implies several Hypotheses regarding the relative position of posted prices and auctions in the (p, R)–plot (for an illustration see Figure 3). Proposition 2 uses this single-crossing result to establish a pure strategy equilibrium in which auctions are better than posted prices for seller i if and only if r_i is below $\tilde{r}_i$ and the corresponding optimal selling probability exceeds a threshold $\hat{p}_i$. If auctions (posted prices) are chosen by sellers with high (low) optimal selling probabilities, the observed selling probabilities of auctions and posted prices should differ significantly.

Hypothesis 3 *Selling probabilities for posted prices are lower than selling probabilities for auctions.*

Furthermore, the optimality of auctions compared to posted prices beyond a threshold selling probability $\hat{P}$ also implies that the two mechanisms should differ in the vertical dimension, i.e. regarding the revenue in case of trade and, as a consequence, regarding the start prices.

Hypothesis 4 *Start prices in auctions are below posted prices.*

Hypothesis 5 *Successful posted prices are above final auction prices.*

In our model, posted prices are only offered if bidders incur hassle cost of participating in an auction, which implies that bidders prefer buying at a posted price to participating at an auction with equally high start price. Hence, we should expect posted prices to be sold more frequently as compared to equally high start prices.

Hypothesis 6 *Posted prices are more frequently sold than auctions with equally high start prices.*

Finally, due to the single-crossing property of (p, R)–plots, all auctions with selling probabilities above (below) that at the intersection of (p, R)–plots are superior (inferior) to posted prices with the same selling probability. Hence, Proposition 2 concludes that high valuation sellers (i.e. sellers that prefer low selling probabilities and high revenues in case of selling) offer posted prices and low valuation sellers (i.e. sellers that prefer high selling probabilities and low revenues in case of selling) offer auctions.

Our most important hypothesis is thus that, when selling probabilities are the same for both selling modes, auctions lead to higher expected revenues for high selling probabilities, while posted prices yields higher expected revenues for low selling probabilities:

Hypothesis 7 *For low selling probabilities, posted prices are superior. For high selling probabilities, auctions are superior.*

3 Empirical Analysis

3.1 Data

We use data from secondary ticket sales for the EURO 2008, the European Football (Soccer) Championship for national teams. 16 teams participated in this major European sport event, which took place in Austria and Switzerland from June 7th to June 29th. Tickets were valid for a particular match of the championship. Altogether, 31 matches were played, including 24 matches in the preliminary round of four teams each in four groups playing round robin. The best two teams of each group qualified for one of the four quarter finals, from which on teams succeeded to the semi-final and the final in a knock-out-system.

As our model emphasizes the role of seller heterogeneity for the optimal choice of a trade mechanism, ticket sales seems to be a good testing ground for at least three reasons: First, for many items sold on eBay such as computer hardware, there is a competitive fringe as they can also be purchased in retail stores, for instance. This reduces the impact of buyers' and sellers' heterogeneity as, independently of their own valuations, the competitive fringe establishes an upper bound on the buyers' willingness to pay and a lower bound on the sellers' reservation value.

Second, tickets are perishable goods which we consider as an advantage for investigating the effects we are interested in: A durable good which has not been sold can immediately be posted again with a similar expected revenue for the seller. Thus, a seller's ex ante valuation of not selling the item at an auction has a lower bound at the expected revenue times the discount factor for the duration of the auction (which is only a couple of days at eBay). By contrast, in the extreme case of a good that completely perishes soon after the end of an auction or posted price offer, the seller's valuation of an unsold item is equal to her utility when consuming the item herself should there be enough time left to do so. As we are interested in the heterogeneity of sellers' preferences, a perishable good seems most suitable for our analysis.

Third, seller heterogeneity has the strongest impact on mechanism choice if the number of buyers exceeds the number of sellers. With just a few buyers, sellers are rather limited in trading-off selling probabilities and revenues conditional on selling. Although we cannot identify the number of buyers for each event in our data set, it is straightforward that the number of buyers largely exceeds the number of sellers. Almost all items with a posted price up to twice the original price are sold. Besides, at the first stage of the official ticket sale by the UEFA, demand exceeded supply by a factor of about 33.[10]

Tickets were originally sold by the United European Football Association (UEFA) and the regarding national football associations. Because of excess demand, tickets were

[10]See e.g. http://www.seetheglobe.com/modules/news/article.php?storyid=1161

distributed in a lottery among the applicants in the end of January 2008.[11] In each match, there were three categories of tickets with regard to the quality of the seats. Original prices differed between qualities and varied form €45 for quality 3 to €110 (quality 1) for matches in the preliminary round, up to €550 for the highest quality 1 in the final. A seller's reservation value r_i in the model can be interpreted as the utility from watching the match in the stadium herself, which is, of course, unobservable to us.

eBay provided the main platform for re-sales, and created an own category for the EURO 2008 on their German website (ebay.de, Tickets > Sport > Fussball EM 2008). By using the software tool BayWotch which automatically archives items offered on Ebay, we started collecting data on February 1, 2008 and distinguish postings with respect to the match and the ticket category. Sellers could decide on the selling mode. We restrict our analysis to the comparison of pure auctions and posted prices and do not take mixed options into account.[12] Our final data set includes more than 12,000 observations with 87% auctions and 13% posted prices (see Table 1 for an overview of variables and descriptive statistics). In auctions, sellers could specify start prices (other than the automatical start price of €1). To save notation, we will refer to both the start price in an auction and the posted price as the *start price*. In order to make prices for different matches and categories of seat quality comparable, we measure all start prices and selling prices as multiples of the original price, and we refer to these multiples as (relative) mark-ups. In the following, we therefore always use the terms start price and selling price in this relative way.

Insert Table 1 about here

The first three lines of Table 1 show the descriptives of the variables that we are mainly interested in, that is, start prices, fraction of items sold and selling prices. The distribution of ticket categories represents their relative availability in the stadiums. The majority of offers contains tickets of the medium category 2 and 20 percent those of the top category 1. Most offers encompass more than one ticket. We aggregate sales with three and more tickets to one category due to the limited number of observations.[13] As the final price is likely to be affected by the number of competing offers, we control for

[11]Tickets were not auctioned due to distributional issues.

[12]Our original data set included about 14% of mixed offers where an auction could be terminated by a buy-now option. These offers are excluded in our analysis.

[13]The dominance of packages of two tickets can be attributed to two reasons. First, the likelihood of receiving more than two tickets in the original allocation by the UEFA was low. Second, most football fans prefer buying at least two tickets in order to share the experience.

the number of simultaneous homogeneous offers in terms of tickets for a certain match and a certain quality running at the same time. On average, there are 72 homogeneous offers at one point of time.

Furthermore, the buyers' willingness to pay (wtp) is likely to depend on the days left to the actual match. Straightforwardly, one might assume that, due to higher attention, the wtp is first increasing when the match approaches. A few days before the match starts, however, the wtp decreases as hassle costs for exchanging the tickets in due time become very high. Therefore, we will also take the square of days left until the start of the match into account.

For auction duration, one might presume that longer auctions will attract more consumers, but there may be countervailing effects as potential buyers might be reluctant to enter auctions ending only in some days. Sellers have the choice among one, three, five, seven and ten days, and both in auctions and with posted prices, about 40% of sellers choose either one or three days.[14] Finally, the literature has shown that prices may depend on the duration of postings and on the weekday and time when an auction ends.[15] It has been argued that bidders may be more active in their leisure time, so that demand and selling prices should be highest for auctions ending at the weekend and/or in the evening. In our sample, a majority of postings ends on Sundays (27%) and during the evening hours between 6 and 10 p.m. (69%).

3.2 A First Look at Prices and Selling Probabilities

Recall from Section 2.6 that Hypotheses 1 and 2 refer to a separate analysis of auctions and posted prices, while all other hypotheses compare the two mechanisms. In all regressions in Table 2 and thereafter, standard errors are clustered at the match level. The first two columns of Table 2 show that the selling probabilities are significantly decreasing in start prices and posted prices, respectively (see Hypothesis 1).

Insert Table 2 about here

In the next two columns, the dependent variable is the actual selling price in auctions. In column 3, we run a simple OLS model. Then, the start price is highly significantly positive as predicted by Hypothesis 2a. However, the OLS estimation only takes into

[14]We aggregated periods of one and three days in one variable which we will use as reference category in our regressions. Disaggregating between one and three days has no impact.

[15]See, for instance, (Lucking-Reiley et al. 2007, p. 230).

account sold items, whereas unsold items, for which we would observe low prices if it was not for the high start price, are neglected. We, therefore, follow the literature (see, for instance Lucking-Reiley et al. (2007) or, more recently, Goncalves (2013)) by using censored normal regressions with variable censoring point to estimate unconditional revenues. Thereby, we account for the fact that the observed prices are left-censored by the start price. In line with Hypothesis 2b and in support of the way we model market clearing prices as the result of cross-bidding, we then find no impact of start prices on final auction prices.

We now proceed to the comparison of posted prices and auctions. In line with *Hypothesis 4*, Table 1 on the descriptive statistics shows that the mean posted price amounts to more than the quintuple of the original price (5.73), while the mean start price for auctions is far below one (around 0.34). The main reason for this huge difference is that around 86% of auction sellers do not set a start price, and the minimum start price of €1 is automatically assigned to these auctions. When restricting attention to start prices weakly above the original ticket price, the average mark-up in auctions is about four, so that start prices are high if applied at all. Furthermore, in line with *Hypothesis 3* and findings by (Hammond 2010, Table 6, Column (4)), most tickets offered in auctions are sold (97.1%), while only 54.6% of all posted prices were successful. If items with posted prices are sold, however, selling prices are higher with posted prices; see *Hypothesis 5*.

We now test our hypotheses on the comparison of auctions and posted prices by using the control variables listed in Table 1. As reference categories, we use sales with one ticket, the highest category of ticket quality (category 1), the shortest auction duration, and posted prices. We run a simple OLS regression for start prices (model 1), a binary probit for the selling probability (model 2), and a censored normal regression for selling prices (model 3). All regressions include match dummies.

Insert Table 3 about here

Model 1 shows that the impression from the descriptive statistics extends to the multivariate analysis, thereby confirming *Hypothesis 4* that start prices in auctions are, on average, below posted prices. Start prices are higher for tickets of inferior categories and for bundles of tickets as people prefer to watch matches with friends. Furthermore, the start price is slightly lower when the number of simultaneous auctions for the same match is high.

The coefficients of the binary probit estimations on the selling probability in column 2 are marginal effects, calculated at the mean of all variables. In line with *Hypothesis*

3, the selling probability is about 40 percentage points higher for auctions. Given that the selling probability for posted prices is about 57%, this amounts to a large increase by about 70%. The selling probability is decreasing in the time left to the match and in the number of simultaneously running offers, and increasing in auction duration.

In line with Hypothesis 5, the censored normal regression (model 3 in Table 3) shows that the selling price is considerably lower for auctions. Selling prices are decreasing in the remaining time to the match at a decreasing rate, and also decreasing in the number of simultaneously running offers. Tickets of lower quality and bundles of tickets yield higher relative mark-ups. Sales that end in evening hours and on Sundays gain lower revenues indicating an excess supply at these times, which has previously been found in Simonsohn (2010), for instance.

Summing up, Table 3 is consistent with the standard trade-off stressed in the literature that posted-price items are sold at higher prices, but with a lower probability.[16] However, start prices, selling probabilities and selling prices are not independent from each other. We will empirically explore these interdependencies in the following section.

3.3 A Closer Look at the Probability-Price Trade-Off

To provide more detailed information on the impact of start prices, Table 4 disaggregates by intervals. This is useful as start prices are considerably higher for posted prices, so that the disaggregation sheds light on the impact of selling modes for similar start prices.

Insert Table 4 about here

For both selling modes, Table 4 shows the expected clear inverse relation between the start price and the selling probability. With one exception for posted prices, the selling probability is consistently decreasing from category to category. For auctions, the selling probability is almost 100% for mark-ups below two, which can be attributed to the fact that most auctions in this category entail the minimum start price of one Euro only. Selling probabilities then decrease to less than 19% for mark-ups above six. For posted prices, the impact of the start price is less pronounced as the selling probability is still 40% even for start prices above six.

Recall that model 3 in Table 3 shows that, when considering the whole data set and without controlling for start prices, the mark ups for successful auctions are considerably

[16] Halcoussis and Mathews (2007), Hammond (2010), Hammond (2013), Bauner (2015).

lower compared to posted prices. We now disaggregate the analysis by separating the regressions for the different categories of start prices in Table 4.

Insert Table 5 about here

For easier reference, the last column repeats the aggregated regression from model 3 in Table 3, which shows that auctions sell at lower prices than posted-price offers do. Notably, however, the coefficients for the auction dummy are largely heterogenous across the intervals of start prices: For the two intervals with the lowest start prices, the auction dummy is significantly positive, but it is insignificant for all other intervals. Summarizing, Table 5 shows that auctions sell at lower prices than posted-price items do, but that this effect is driven by lower start prices. To gain a better understanding on the actual impact of the selling mode on selling probabilities and revenues, we thus need to control for the start price.

Insert Table 6 about here

Table 6 reports the results of probit estimations on selling probabilities. For easier reference, model 1 repeats model 2 of Table 3 and does not control for the start price. It shows a highly significant positive effect of the auction dummy on the selling probability. However, controlling for the logarithm of the start price in model 2 reverses the result and yields a significantly negative coefficient.[17] Hence, if start prices were the same, posted prices would have the higher selling probability. This confirms Hypothesis 6 and is in line with our theory that at least some buyers strictly prefer a posted-price transaction over an auction with the same start price.

Probit model 2, in which we control for the selling mode, assumes that the regressors have similar effects on the selling probability across selling modes and is given by

$$p_i = \begin{cases} \Phi\left(\hat{\beta}_0 + \hat{\beta}_S \ln S_i + \hat{\beta}_A + \hat{\beta}_{\mathbf{x}} \mathbf{x_i}\right), & \text{if } i \text{ is auctioned;} \\ \Phi\left(\hat{\beta}_0 + \hat{\beta}_S \ln S_i + \hat{\beta}_{\mathbf{x}} \mathbf{x_i}\right). & \text{if } i \text{ is offered at a posted price,} \end{cases} \tag{1}$$

Thereby, $\Phi(.)$ denotes the standard normal distribution, S_i is the start price and $\mathbf{x_i}$ the observable characteristics of item i, and $\hat{\beta}_0$, $\hat{\beta}_S$, $\hat{\beta}_A$ and $\hat{\beta}_{\mathbf{x}}$ are the parameter estimations

[17]We use the logarithm to account for the nonlinear relationship between the impacts of the start price and other characteristics of the item: While the start price is irrelevant even for a winning bidder's utility as long as there are at least two bidders whose valuations exceed it, the item's characteristics are always relevant for the winning bidder, and the selling mode may even be relevant upon mere participation.

for the constant, the start price, the auction dummy and the items' characteristics, respectively. As the impact of the control variables may well differ between the two sales modes, models 3 and 4 consider auctions and posted prices separately. Note that models 3 and 4 are identical to models 1 and 2 in 2. We will later refer to the notation used in the following formalization of the estimated selling probabilities for the respective subsamples:

$$p_i^A = \Phi\left(\hat{\beta}_0^A + \hat{\beta}_S^A \ln S_i + \hat{\beta}_{\mathbf{x}}^{\mathbf{A}} \mathbf{x_i}\right) = \Phi(\hat{y}_i^A) \tag{2}$$

$$p_i^F = \Phi\left(\hat{\beta}_0^F + \hat{\beta}_S^F \ln S_i + \hat{\beta}_{\mathbf{x}}^{\mathbf{F}} \mathbf{x_i}\right) = \Phi(\hat{y}_i^F) \tag{3}$$

where $\hat{y}_i^k$ denotes the predicted argument of the probability function for the regression based on the data for selling mode k. An important result is that the start price particularly matters for auctions: increasing the logarithm of the mark-up for the start price by one reduces the selling probability for auctions by 63 percentage points in auctions compared to 24 percentage points with posted prices.

3.4 Selling Probabilities and the Ranking of Selling Modes

In our theory, the relationship between expected revenue in case an item is sold and the selling probability is represented by a (p, R)–plot for each selling mode. The main hypothesis derived from the model is that there is a single cutting point for the (p, R)–plots for auctions and posted prices, so that posted prices are superior if and only if the selling probability is below some probability $\widehat{p}$. The scatterplot in Figure 4 indicates that this relationship may also hold empirically: For every observation in our dataset, we predicted the selling probability using model (3) (model (4)) of Table 6 for auctions (posted prices), and the final price conditional on sale for auctions using model (3) of Table 2. The blue (red) dots in Figure 4 represent all auctions (posted prices) in our dataset in this way. The respective fitted lines intersect, with posted prices yielding higher predicted final prices than auctions for probabilities below the intersection.

However, the fitted lines in Figure 4 are no (p, R)–plots in the same sense as in the theoretical model, as the predictions of selling probabilities and final prices were made based on different items with different observable characteristics. By contrast, what a seller is interested in is a prediction of the expected final price of the same item when using the counterfactual selling mode with an identical selling probability. In order to analyze the ranking of the two selling modes for identical selling probabilities, we first calculate, for each item offered in an auction, the posted price that would have matched the auction's selling probability. Whenever an auction yields a higher revenue for the same selling probability than a posted price does, then a seller would have been better off by choosing an auction rather than a posted price (and vice versa). We then regress the difference between the actual auction price and the estimated posted price on the auction's start price, which serves as a proxy for the selling probability. This difference can be interpreted as the vertical distance between the (p, R)–plots for auctions and posted prices.

For the first step, recall the Probit regression in model 2 of Table 6. Suppose that observation i is an auction, so that the upper case of Equation (1) applies. We calculate the posted price F_i at which the item would have had to be offered so as to keep the selling probability constant by substituting F_i for S_i in the lower case of (1), and equate both cases. Solving for F_i yields

$$F_i = e^{\hat{\beta}_A/\hat{\beta}_S} S_i. \tag{4}$$

Hence, if R_i denotes the selling price of the auction, the excess selling price of auction i over a hypothetical posted-price offer with the same selling probability, denoted by ESP_i, is

$$ESP_i = R_i - F_i = R_i - e^{\hat{\beta}_A/\hat{\beta}_S} S_i. \tag{5}$$

Model 1 of Table 7 estimates this excess selling price ESP_i for all auctions in our dataset by using the logarithmic start price as an independent variable along with the usual control variables. Since (p, R)–plots refer to revenue *conditional on sale*, the regressions in Table 7 include only sold items and thus require no censored normal regression. As only sold items are considered, the number of observations is reduced to $n = 10,409$. The coefficient of the logarithmic start price is highly significantly negative, that is, the excess return of auctions compared to posted prices with the same selling probability decreases in start prices. Thus, the lower the selling probability a seller is willing to accept by choosing a higher start price, the better is the performance of posted prices compared to auctions. This confirms our main Hypothesis 7 derived from the theoretical model.

Insert Table 7 about here

Model 1 of Table 7 estimates the impact of the start price on the difference between the selling price in the auction and the hypothetical posted price under the assumption that the independent variables have the same influence under both selling modes. However, comparing the separate probit regressions for auctions and posted prices (models 3 and 4 of Table 6) reveals that the convex shape of the selling probability in the time remaining until kickoff in model 2 is entirely driven by posted prices. For auctions, on the other hand, the weakly significant coefficient of the quadratic remaining time suggests, if anything, a concave pattern.

As a robustness check, we therefore redo the whole exercise with estimates from the two separate Probit regressions given in models 3 and 4 of Table 6. As a preliminary step, we use the estimates from model 3 to predict the argument $\hat{y}_i^A$ of the probability function in (2) for both auctions and posted prices. Similarly, we use the estimates from model 4 to predict the corresponding $\hat{y}_i^F$. Again, we can calculate the hypothetical posted price F_i' by equating the right-hand sides of (2) and (3):

$$F_i' = e^{(\hat{y}_i^A - \hat{\beta}_0^F - \hat{\beta}^{\mathbf{F}}_{\mathbf{x}} \mathbf{x_i})/\hat{\beta}_S^F} = e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F} \tag{6}$$

The excess selling price of auction i over a hypothetical posted-price offer with the same selling probability is then

$$ESP_i' = R_i - F_i' = R_i - e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F}. \tag{7}$$

Model 2 of Table 7 shows that our main result that the excess return of auctions decreases in the start price (and thus increases in the induced selling probability) is robust.[18] The impact of our control variables is also basically the same in both estimations, with the exception of the remaining time to the match. The difference of this variable is intuitive as the remaining time is less important for posted prices due to a lower time difference between posting and the actual transaction.

We have argued above that the difference between the actual revenue of an auction and the hypothetical posted price that would have been sold with the same probability, can be interpreted as the vertical distance between the (p, R)–plots of auctions and posted prices. The negative sign of the coefficient for the start price in Table 7 confirms the single crossing result from the theoretical model. Another way of illustrating how our results support the model is to directly look at (p, R)–plots generated by our data. For the specifications of our respective empirical models, our parameter estimates can be used to derive the shapes of these plots for any combination of item characteristics.

For instance, suppose that selling probabilities for auctions and posted prices are given by equations (2) and (3), respectively. Then, the (p, R)–plot for posted prices is

[18] One might object that, due to the high number of auctions without start prices, these auctions may drive the results in a trivial way. However, applying the whole procedure set out in this subsection to a subsample that excludes auctions without a start price yields qualitatively the same results, which are given in the appendix in Tables 8 (which corresponds to the main Table 6) and 9 (corresponding to Table 7).

immediately given by the inverse of (3), as revenue conditional on sale is equal to the start price. As this will typically not be the case for auctions, we first need to estimate the relationship between start prices and revenue conditional on sale. The empirical model for this estimation is:[19]

$$R_i = \hat{\alpha}_0 + \hat{\alpha}_S S_i + \hat{\alpha}_{\mathbf{x}} \mathbf{x_i}. \tag{8}$$

Solving (8) for S_i and substituting for S_i in (2) yields the inverse of the (p, R)–plot for auctions. Figure 5 displays the (p, R)–plots obtained in this way for the case where all continuous variables are at their means and all categoric variables are at the reference category. Again, the single crossing result with the (p, R)–plot for auctions cutting that for posted prices from below is confirmed.

4 Concluding Remarks

Our model of competing sellers' choices of mechanism confirms the well-known superiority of auctions in the absence of auction specific hassle costs and demonstrates the single-crossing of optimal mechanisms in the presence of hassle costs. In our model, these results are based on our assumption that competing auctions retrieve market clearing prices, which has been shown to emerge as an equilibrium in a model of cross-bidding between auctions by Peters and Severinov (2006), and the way in which we have integrated posted prices in the determination of market clearing prices. In this sense, our model gives a "better shot" at auctions than the usual approach of the literature that assumes a commitment to a particular mechanism of a particular seller either before or after the buyer learns his own valuation (see McAfee (1993), Peters (1997), Virag (2010), Hammond (2013), or Bauner (2015)). We establish single crossing of revenues for auctions and posted prices in such a setting. Hence, there exists a cutoff valuation such that a seller prefers a posted price if her valuation is above this cutoff, and an auction if it is below the cutoff.

This result is robust to different ways of modeling competition between auctions and posted prices. As already mentioned in the introduction, the same outcome would result from a model where buyers cross-bid over auctions as in Peters and Severinov (2006) and execute a posted price f if and only if the standing bid at the auctions reaches f. The superiority of auctions in the absence of auction specific hassle costs has been established in the literature on competitive mechanism design (see, e.g., McAfee (1993)). Introducing hassle costs for auctions would also lead to an increasing benefit of posted

[19]The result of this estimation is given in Table 10 in the Appendix.

prices for sellers with higher valuations (and the corresponding single-crossing result) in the model of Peters (1997) where buyers first select into a trade mechanism and then start competitive bidding. Unlike in our model (and at odds with Hypotheses 2a) this model would, however, predict that final auction prices depend on starting prices because starting prices influence the sorting of buyers into different trade institutions.

Empirically, we have used ticket sales for the European football championship to test the hypotheses drawn from our model. Our most important result is that, when selling probabilities are identical for the two sales modes, auctions lead to higher expected revenues if and only if selling probabilities are high. This confirms our main Hypothesis 7 from the theoretical model that the (p, R)–plot for auctions cuts that for posted prices from below.

To see the value added of our empirical strategy, recall that a large body of empirical literature has shown that, on average, posted prices yield larger revenues compared to auctions when the items are actually sold, but at the expense of lower selling probabilities. Our theoretical model demonstrates that controlling for selling probabilities is the appropriate way of making competing sellers' revenues from auctions and posted prices comparable to each other. Hence, the empirical strategy follows the theoretical model which identifies the (p, R)–plot and, therefore, the selling mode that maximizes a seller's revenues for her individually optimal selling probability, which is determined by her reservation value.

Let us now add some methodological remarks concerning the link between our model and the empirical analysis. In our model, the reservation values determine the sellers' choice of the selling probabilities in the (p, R)–plot, and thereby also the choice of the sales mechanism. For the empirical analysis, this means that the self-selection to sales modes is driven by a variable that is unobservable to us, and for which we cannot think of a good proxy or instrument. This raises two issues: First, we cannot directly test whether reservation values are in fact decisive for the choice of the mechanism. All we can say is that our empirical results strongly confirm the hypotheses derived from the theory. Furthermore, other papers using inventories as proxies for reservation values (Hammond, 2010) support that self selection is driven by reservation values. In this sense our theory adds to our general understanding of self-selection into different sales modes.

The second potential issue concerns our empirical comparison of the (p, R)–plots for the two sales modes. Our main result is that a seller who wants to implement a high selling probability gets higher expected revenue with auctions, while higher revenues are realized with posted prices for low selling probabilities. If, as allowed by our model, sellers' valuations are drawn from different probability distributions, each seller faces a different distribution of rival sellers' valuations and, therefore, considers a different (p, R)–plot. In this sense, our estimation compares an average seller's (p, R)–plot for both modes of sale. For such an average seller the (unobserved) reservation value determines the optimal selling probability, but for a given selling probability, a mechanism is superior regardless of the seller's valuation.

While unobserved heterogeneity of reservation values themselves is thus no concern for our empirical strategy, a potential endogeneity problem arises when these reservation values are correlated with other unobservable attributes of sellers, and when those attributes influence revenue in the two sales modes in different ways even *for identical selling probabilities*. To see this, recall that, when we estimate revenue in auctions by controlling for selling probabilities, we can only use data from sellers who self-selected into auctions. When we then estimate the *hypothetical* revenue of a posted-price seller in an auction, we assume that this seller faces the same (p, R)–plot as auction sellers do. However, we cannot fully exclude that posted-price sellers would behave in a different way in auctions with regards to side factors influencing the revenue, such as the auction duration and the day on which an auction ends. If the sellers' attributes which determine these side factors are correlated with the factors determining their desired selling probabilities, then the revenue of a posted-price seller switching to an auction can be slightly different from the average revenue estimated from our auction data, even after controlling for the selling probability. Note, however, that the main attributes that buyers are interested in, such as the category and the number of tickets, are observable to us, so that we can control for them. Hence, the assumption that sellers face identical (p, R)–plots seems reasonable.

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Table 1: Summary Statistics.

	Whole sample ($n = 12,315$)	Auctions ($n = 10,715$)	Posted prices ($n = 1,600$)
Start price	1.038	0.337	5.728
	(5.858)	(1.282)	(11.217)
Selling frequency	0.916	0.971	0.546
Selling price (if sold)	4.035	3.963	4.892
	(4.169)	(3.872)	(6.917)
Category 1	0.202	0.199	0.221
Category 2	0.509	0.513	0.484
Category 3	0.289	0.288	0.295
1 Ticket	0.142	0.141	0.147
2 Tickets	0.745	0.771	0.575
3+ Tickets	0.113	0.088	0.278
Simultaneous homogenous offers	72.00	72.77	66.86
	(4694.97)	(4676.01)	(4794.57)
Remaining time (until kickoff / days)	20.78	20.48	22.75
Duration 1 or 3 days	0.421	0.423	0.404
Duration 5 days	0.188	0.195	0.144
Duration 7 days	0.241	0.252	0.171
Duration 10 days	0.150	0.130	0.281
End of auction on			
Saturday	0.103	0.101	0.116
Sunday	0.271	0.288	0.154
Evening (6 to 10 p.m.)	0.686	0.713	0.504

Variance in brackets.

Table 2: Selling Probabilities and Prices for Given Selling Mode.

	(1)	(2)	(3)	(4)
Dependent Variable	Status (1=sold)	Status (1=sold)	Selling Price	Selling Price
Selling mode	Auctions only	Posted Prices only	Auctions only	Auctions only
Status	All Items	All Items	Sold Items only	All Items
ln Start Price	-0.6258***	-0.2455***		
	(0.0353)	(0.0411)		
Start Price			0.0767**	-0.0163
			(0.0297)	(0.0266)
Days left to match	0.0400	-0.0367***	-0.1138	-0.1084
	(0.0299)	(0.0127)	(0.0952)	(0.0943)
Days left to match squared	-0.0036	0.0022**	0.0040	0.0035
	(0.0023)	(0.0009)	(0.0073)	(0.0071)
Number of competing offers	-0.0004	-0.0010***	-0.0053***	-0.0052***
	(0.0002)	(0.0003)	(0.0011)	(0.0011)
End of auction (dummies)				
Saturday	0.0152	-0.0222	0.0978*	0.1017*
	(0.0281)	(0.0179)	(0.0553)	(0.0554)
Sunday	-0.0194	-0.0480**	-0.0627**	-0.0631**
	(0.0268)	(0.0241)	(0.0273)	(0.0280)
Evening (6 to 10pm)	-0.0577**	-0.0069	-0.0459	-0.0585
	(0.0250)	(0.0068)	(0.0353)	(0.0360)
Ticket quality (base: top quality)				
Medium quality	0.0454	0.0575***	0.6071***	0.5987***
	(0.0431)	(0.0173)	(0.0947)	(0.0930)
Regular seats	0.2870***	0.1108***	2.7241***	2.7292***
	(0.0326)	(0.0184)	(0.1564)	(0.1536)
Number of offered tickets (base: 1)				
2 tickets	0.0633	0.0551***	0.6549***	0.6528***
	(0.0552)	(0.0176)	(0.1442)	(0.1478)
3 or more tickets	0.0415	0.0322***	0.4918***	0.4842***
	(0.0515)	(0.0107)	(0.1615)	(0.1636)
Duration of posting (base: 3 days)				
5 days	0.0837**	0.0210**	0.2845***	0.2961***
	(0.0366)	(0.0099)	(0.0904)	(0.0936)
7 days	0.1009***	0.0306***	0.3552***	0.3658***
	(0.0345)	(0.0110)	(0.0908)	(0.0917)
10 days	0.0562	0.0508***	0.4615***	0.4635***
	(0.0488)	(0.0147)	(0.0793)	(0.0818)
Intercept			2.5962***	2.6108***
			(0.1441)	(0.1426)
Match Dummies	Yes	Yes	Yes	Yes
Observations	10,565	1,600	10,409	10,715

Panels (1) and (2) of the table display marginal effects calculated at $\ln S_i = 1$ and at the mean of all other variables. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 3: Determinants of Start Prices, Selling Probabilities and Selling Prices.

	(1)	(2)	(3)
Dep. Variable	Start Price	Sold (1 = yes)	Selling Price
Estimation	OLS	Probit	Censored Normal
Auction (1=yes)	-5.2954***	0.4091***	-0.4824***
	(0.2239)	(0.0182)	(0.0520)
Days left to match	0.0094	-0.0071**	-0.1151
	(0.0283)	(0.0034)	(0.0907)
Days left to match squared	-0.0021	0.0004	0.0038
	(0.0023)	(0.0003)	(0.0068)
Number of competing offers	-0.0008	-0.0002***	-0.0056***
	(0.0007)	(0.0001)	(0.0011)
End of auction (dummies)			
Saturday	0.0582	-0.0095	0.1075*
	(0.0442)	(0.0062)	(0.0604)
Sunday	-0.0114	-0.0102**	-0.0758***
	(0.0344)	(0.0041)	(0.0267)
Evening (6 to 10pm)	-0.1534***	0.0022	-0.0647**
	(0.0384)	(0.0046)	(0.0309)
Ticket quality (base: top quality)			
Medium quality	0.1870***	-0.0078	0.5853***
	(0.0591)	(0.0081)	(0.0951)
Regular seats	0.6629***	-0.0041	2.7447***
	(0.0746)	(0.0036)	(0.1562)
Number of offered tickets (base: 1)			
2 tickets	0.1280*	0.0058	0.6794***
	(0.0679)	(0.0052)	(0.1394)
3 or more tickets	0.2368**	-0.0086	0.5197***
	(0.0972)	(0.0067)	(0.1499)
Duration of posting (base: 3 days)			
5 days	-0.0236	0.0166**	0.2935***
	(0.0581)	(0.0066)	(0.0957)
7 days	-0.0161	0.0206***	0.3799***
	(0.0508)	(0.0059)	(0.0940)
10 days	0.0791	0.0159**	0.4928***
	(0.0726)	(0.0080)	(0.0928)
Intercept	5.1128***		2.9360***
	(0.1805)		(0.1268)
Match Dummies	Yes	Yes	Yes
Observations	12,315	12,315	12,315

Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively. For model (2), marginal effects calculated at the mean of all variables are reported.

Table 4: Probability of Sale and Selling Prices of Auctions and Posted Prizes by Start Price Categories.

Start Price	Auctions					Posted Price				
	Number	Share in Auctions	Mean Start Pr.	% Sold	Mean Selling Pr.	Number	Share in Posted Pr.	Mean Posted Pr.	% Sold	Mean Selling Pr.
$S < 2$	10,050	0.938	0.09	0.997	3.94	56	0.035	1.46	0.929	1.45
			(0.11)		(3.83)			(0.22)		(0.23)
$2 \leq S < 3$	257	0.024	2.46	0.778	3.78	177	0.111	2.59	0.797	2.60
			(0.07)		(2.78)			(0.07)		(0.07)
$3 \leq S < 4$	158	0.015	3.40	0.608	4.73	275	0.172	3.45	0.644	3.44
			(0.08)		(3.33)			(0.08)		(0.08)
$4 \leq S < 5$	98	0.009	4.41	0.531	5.27	249	0.156	4.48	0.494	4.48
			(0.08)		(2.23)			(0.09)		(0.10)
$5 \leq S < 6$	71	0.007	5.38	0.380	6.03	231	0.144	5.48	0.593	5.48
			(0.12)		(1.07)			(0.10)		(0.10)
$6 \leq S$	81	0.008	8.35	0.185	9.35	612	0.383	8.65	0.399	7.88
			(9.46)		(12.48)			(13.14)		(8.24)
All	10,715	1.000	0.34	0.971	3.96	1,600	1.000	4.89	0.546	4.89
			(1.28)		(3.87)			(11.22)		(6.92)

Variance in brackets.

Table 5: Estimations on Selling Prices by Start Price Categories.

	$S < 2$	$2 \leq S < 3$	$3 \leq S < 4$	$4 \leq S < 5$	$5 \leq S < 6$	$6 \leq S$	All
Auction (1=yes)	1.1087***	0.3205**	0.1354	0.1822	-0.1085	-1.0428	-0.4824***
	(0.2170)	(0.1597)	(0.1473)	(0.1293)	(0.0863)	(0.6572)	(0.0520)
Days left to match	-0.1045	0.0182	-0.0522	-0.1338	-0.1256***	-0.8242***	-0.1151
	(0.0948)	(0.0857)	(0.0813)	(0.1002)	(0.0426)	(0.1862)	(0.0907)
Days left to match squared	0.0034	-0.0031	-0.0007	0.0078	0.0063**	0.0545***	0.0038
	(0.0073)	(0.0086)	(0.0050)	(0.0076)	(0.0025)	(0.0160)	(0.0068)
Number of competing offers	-0.0051***	-0.0025	-0.0034*	-0.0037**	-0.0030***	-0.0205***	-0.0056***
	(0.0011)	(0.0016)	(0.0018)	(0.0017)	(0.0010)	(0.0032)	(0.0011)
End of auction (dummies)							
Saturday	0.0826	0.0728	0.1753	0.2309	0.0104	0.1973	0.1075*
	(0.0603)	(0.1685)	(0.2673)	(0.2099)	(0.1059)	(0.5166)	(0.0604)
Sunday	-0.0628**	-0.0436	-0.0712	-0.0094	-0.1151	-0.6678	-0.0758***
	(0.0281)	(0.1036)	(0.0973)	(0.1243)	(0.1128)	(0.5248)	(0.0267)
Evening (6 to 10pm)	-0.0606*	0.1209	-0.0773	0.0732	0.0624	-0.5784*	-0.0647**
	(0.0340)	(0.1005)	(0.0824)	(0.0787)	(0.0949)	(0.3252)	(0.0309)
Ticket quality (base: top quality)							
Medium quality	0.6052***	0.1134	0.2681**	0.1933**	0.2358**	0.1234	0.5853***
	(0.0956)	(0.1406)	(0.1320)	(0.0850)	(0.1126)	(0.8277)	(0.0951)
Regular seats	2.7382***	1.4344***	1.4105***	0.8409***	0.9959***	2.7233***	2.7447***
	(0.1593)	(0.3276)	(0.2912)	(0.2072)	(0.1700)	(0.6961)	(0.1562)
Number of offered tickets (base: 1)							
2 tickets	0.6547***	-0.0914	0.5014*	0.3880**	0.4773***	1.3441**	0.6794***
	(0.1399)	(0.2407)	(0.3022)	(0.1671)	(0.1159)	(0.6346)	(0.1394)
3 or more tickets	0.4792***	0.0174	0.4790*	0.3343**	0.4107***	0.6720	0.5197***
	(0.1621)	(0.2935)	(0.2829)	(0.1418)	(0.0910)	(0.6333)	(0.1499)
Duration of posting (base: 3 days)							
5 days	0.2820***	0.4139***	0.3988**	0.1178	0.3174*	-0.5968	0.2935***
	(0.0940)	(0.1565)	(0.2010)	(0.1024)	(0.1638)	(0.4309)	(0.0957)
7 days	0.3519***	0.3571***	0.0963	0.2560**	0.2709***	0.1956	0.3799***
	(0.0955)	(0.1332)	(0.1653)	(0.1289)	(0.0915)	(0.5244)	(0.0940)
10 days	0.4415***	0.5989**	0.5327***	0.1584	0.3830***	0.4485	0.4928***
	(0.0842)	(0.2358)	(0.1749)	(0.1478)	(0.0923)	(0.3159)	(0.0928)
Intercept	1.5135***	2.4889***	2.6176***	3.4805***	4.9319***	4.0718***	2.9360***
	(0.2741)	(0.1490)	(0.5077)	(0.2308)	(0.1505)	(1.0892)	(0.1268)
Match Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,106	434	433	347	302	693	12,315

The dependent variable is the selling price, and the estimations are censored normal. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 6: Probit Estimations on Selling Probabilities (1=sold).

Selling mode	(1) All	(2) All	(3) Auctions only	(4) Posted Prices only
Auction (1=yes)	0.4091***	-0.1169***		
	(0.0182)	(0.0196)		
ln Start Price		-0.5735***	-0.6258***	-0.2455***
		(0.0284)	(0.0353)	(0.0411)
Days left to match	-0.0071**	-0.0427**	0.0400	-0.0367***
	(0.0034)	(0.0176)	(0.0299)	(0.0127)
Days left to match squared	0.0004	0.0023*	-0.0036	0.0022**
	(0.0003)	(0.0012)	(0.0023)	(0.0009)
Number of competing offers	-0.0002***	-0.0016***	-0.0004	-0.0010***
	(0.0001)	(0.0003)	(0.0002)	(0.0003)
End of auction (dummies)				
Saturday	-0.0095	-0.0207	0.0152	-0.0222
	(0.0062)	(0.0237)	(0.0281)	(0.0179)
Sunday	-0.0102**	-0.0588**	-0.0194	-0.0480**
	(0.0041)	(0.0240)	(0.0268)	(0.0241)
Evening (6 to 10pm) (d)	0.0022	-0.0379***	-0.0577**	-0.0069
	(0.0046)	(0.0129)	(0.0250)	(0.0068)
Ticket quality (base: top quality)				
Medium quality	-0.0078	0.1036***	0.0454	0.0575***
	(0.0081)	(0.0306)	(0.0431)	(0.0173)
Regular seats	-0.0041	0.2645***	0.2870***	0.1108***
	(0.0036)	(0.0246)	(0.0326)	(0.0184)
Number of offered tickets (base: 1)				
2 tickets	0.0058	0.1098***	0.0633	0.0551***
	(0.0052)	(0.0307)	(0.0552)	(0.0176)
3 or more tickets	-0.0086	0.0586***	0.0415	0.0322***
	(0.0067)	(0.0215)	(0.0515)	(0.0107)
Duration of posting (base: 3 days)				
5 days	0.0166**	0.0625**	0.0837**	0.0210**
	(0.0066)	(0.0263)	(0.0366)	(0.0099)
7 days	0.0206***	0.0974***	0.1009***	0.0306***
	(0.0059)	(0.0267)	(0.0345)	(0.0110)
10 days	0.0159**	0.1000***	0.0562	0.0508***
	(0.0080)	(0.0304)	(0.0488)	(0.0147)
Match Dummies	Yes	Yes	Yes	Yes
Observations	12,315	12,315	10,565	1,600

The dependent variable is Sold (1 = yes). The table displays marginal effects calculated at $\ln S_i = 1$ and at the mean of all other variables. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 7: OLS Estimations on Excess Selling Prices (ESP) of Auctions for Sold Items.

	(1)	(2)
Dep. Variable	ESP	ESP'
ln Start Price	-0.4628***	-0.4299***
	(0.0258)	(0.0228)
Days left to match	-0.1102	-0.0307
	(0.0928)	(0.0907)
Days left to match squared	0.0033	-0.0024
	(0.0071)	(0.0069)
Number of competing offers	-0.0050***	-0.0039***
	(0.0012)	(0.0012)
End of auction (dummies)		
Saturday	0.1076*	0.1329**
	(0.0595)	(0.0624)
Sunday	-0.0760***	-0.0465*
	(0.0264)	(0.0267)
Evening (6 to 10pm)	-0.0553*	-0.0901***
	(0.0283)	(0.0289)
Ticket quality (base: top quality)		
Medium quality	0.7175***	0.6557***
	(0.1006)	(0.1012)
Regular seats	3.0046***	2.9657***
	(0.1613)	(0.1658)
Number of offered tickets (base: 1)		
2 tickets	0.3330**	0.3048**
	(0.1296)	(0.1375)
3 or more tickets	-0.0664	-0.0492
	(0.1389)	(0.1546)
Duration of posting (base: 3 days)		
5 days	0.3041***	0.2989***
	(0.0880)	(0.0922)
7 days	0.3544***	0.3713***
	(0.0925)	(0.0947)
10 days	0.4664***	0.4244***
	(0.0805)	(0.0851)
Intercept	0.2715	0.4520**
	(0.1971)	(0.2146)
Match Dummies	Yes	Yes
Observations	10,409	10,259

Estimations are OLS. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 8: Probit Estimations on Selling Probabilities Excluding Auctions without Start Price.

	(1) All	(2) All	(3) Auctions only	(4) Posted Prices only
Auction (1=yes)	0.2646***	-0.1226***		
	(0.0244)	(0.0207)		
ln Start Price		-0.4469***	-0.7548***	-0.2455***
		(0.0143)	(0.0455)	(0.0411)
Days left to match	-0.0674***	-0.0333**	0.0482	-0.0367***
	(0.0193)	(0.0132)	(0.0366)	(0.0127)
Days left to match squared	0.0043***	0.0018*	-0.0043	0.0022**
	(0.0014)	(0.0009)	(0.0029)	(0.0009)
Number of competing offers	-0.0014***	-0.0012***	-0.0004	-0.0010***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
End of auction (dummies)				
Saturday	-0.0256	-0.0163	0.0184	-0.0222
	(0.0288)	(0.0188)	(0.0343)	(0.0179)
Sunday	-0.0941***	-0.0476**	-0.0234	-0.0480**
	(0.0211)	(0.0210)	(0.0325)	(0.0241)
Evening (6 to 10pm)	-0.0364*	-0.0302***	-0.0723**	-0.0069
	(0.0204)	(0.0101)	(0.0311)	(0.0068)
Ticket quality (base: top quality)				
Medium quality	-0.0016	0.0814***	0.0550	0.0575***
	(0.0409)	(0.0232)	(0.0531)	(0.0173)
Regular seats	-0.0277	0.1951***	0.3209***	0.1108***
	(0.0223)	(0.0158)	(0.0335)	(0.0184)
Number of offered tickets (base: 1)				
2 tickets	0.0282	0.0841***	0.0749	0.0551***
	(0.0304)	(0.0219)	(0.0637)	(0.0176)
3 or more tickets	-0.0141	0.0461***	0.0511	0.0322***
	(0.0270)	(0.0164)	(0.0648)	(0.0107)
Duration of posting (base: 3 days)				
5 days	0.0701*	0.0473**	0.1026**	0.0210**
	(0.0361)	(0.0188)	(0.0461)	(0.0099)
7 days	0.1102***	0.0722***	0.1225***	0.0306***
	(0.0396)	(0.0178)	(0.0417)	(0.0110)
10 days	0.0851	0.0779***	0.0685	0.0508***
	(0.0524)	(0.0228)	(0.0614)	(0.0147)
Match Dummies	Yes	Yes	Yes	Yes
Observations	3,096	3,096	1,476	1,600

The dependent variable is Sold (1 = yes). The table displays marginal effects calculated at $\ln S_i = 1$ and at the mean of all other variables. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 9: OLS Estimations on Excess Selling Prices (ESP) of Auctions for Sold Items, Excluding Auctions without Start Price.

	(1)	(2)
Dep. Variable	ESP	ESP'
ln Start Price	-0.8003***	-0.7569***
	(0.0680)	(0.0656)
Days left to match	-0.1226	0.4513***
	(0.1213)	(0.1281)
Days left to match squared	0.0023	-0.0393***
	(0.0108)	(0.0125)
Number of competing offers	-0.0035***	0.0045***
	(0.0013)	(0.0012)
End of auction (dummies)		
Saturday	0.1411	0.4152***
	(0.1307)	(0.1094)
Sunday	-0.1325	0.1631
	(0.0967)	(0.1038)
Evening (6 to 10pm)	-0.0741	-0.2439***
	(0.0614)	(0.0729)
Ticket quality (base: top quality)		
Medium quality	0.3079**	-0.0965
	(0.1448)	(0.1280)
Regular seats	1.4411***	1.6234***
	(0.1809)	(0.1732)
Number of offered tickets (base: 1)		
2 tickets	0.3384**	-0.0311
	(0.1251)	(0.1244)
3 or more tickets	0.2034	-0.1156
	(0.1603)	(0.1777)
Duration of posting (base: 3 days)		
5 days	0.4028***	0.4620***
	(0.1356)	(0.1322)
7 days	0.2210	0.3419**
	(0.1337)	(0.1598)
10 days	0.4010**	0.0779
	(0.1606)	(0.1598)
Intercept	0.4933***	0.6262***
	(0.1704)	(0.1807)
Match Dummies	Yes	Yes
Observations	1,190	1,170

Estimations are OLS. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 10: OLS Estimation on Revenue for Sold Items.

Start Price	0.0767**
	(0.0297)
Days left to match	-0.1138
	(0.0952)
Days left to match squared	0.0040
	(0.0073)
Number of competing offers	-0.0053***
	(0.0011)
End of auction (dummies)	
Saturday	0.0978*
	(0.0553)
Sunday	-0.0627**
	(0.0273)
Evening (6 to 10pm)	-0.0459
	(0.0353)
Ticket quality (base: top quality)	
Medium quality	0.6071***
	(0.0947)
Regular seats	2.7241***
	(0.1564)
Number of offered tickets (base: 1)	
2 tickets	0.6549***
	(0.1442)
3 or more tickets	0.4918***
	(0.1615)
Duration of posting (base: 3 days)	
5 days	0.2845***
	(0.0904)
7 days	0.3552***
	(0.0908)
10 days	0.4615***
	(0.0793)
Intercept	2.5962***
	(0.1441)
Match Dummies	Yes
Observations	10,409

The dependent variable is revenue conditional on sale, and the estimation is OLS. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

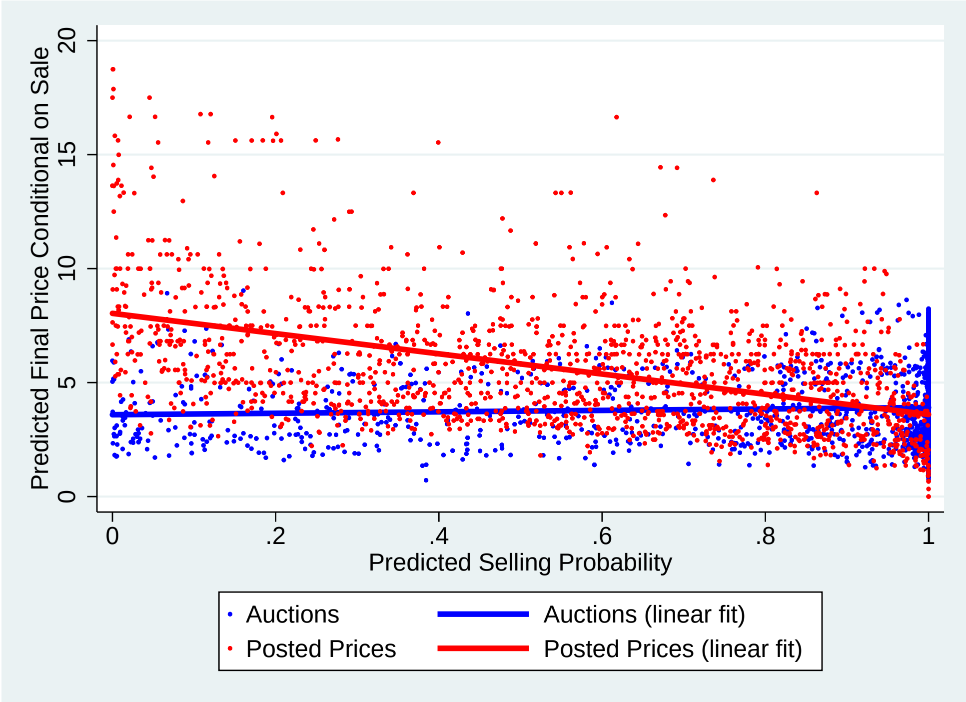

Figure 4: Predicted selling probabilities and final prices conditional on sale for auctions and posted prices.

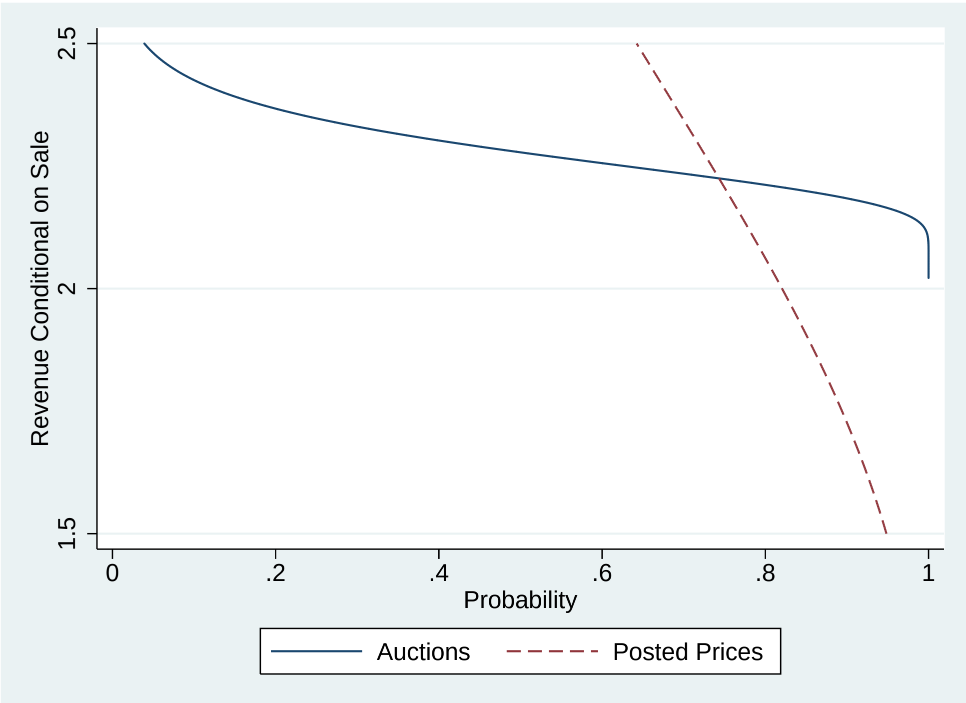

Figure 5: A (p, R)-plot derived from observed bidder behavior.