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# 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.



**JEL Codes:** D43, D44, D82, L13.

**Keywords:** Auctions / bidding, Competing Sellers, Single-Crossing, Posted Prices.


## 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, 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


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[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).

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 monopolistic seller has high opportunity costs of selling the item, it is unlikely that there are at least two bidders with valuations above the seller's opportunity costs. If buyers face hassle costs when participating at an auction, then such a monopolistic seller may strictly prefer offering the item at a posted price rather than at an auction. As a result, posted prices tend to be optimal for a seller with high opportunity costs, whereas auctions are optimal for a seller with low opportunity costs.

In this paper, we extend this analysis to the mechanism choice of *competing* sellers. As suggested by the literature on competing mechanism designers (see the literature review below), it is anything but straightforward to translate results for monopolistic sellers to sellers who compete with the design of their trade mechanism. E.g., it has been shown by Eeckhout and Kircher (2010) that competing sellers may only choose posted prices (rather than auctions) whenever meetings between buyers and sellers are rival.[3] Our model, however, establishes a translation of the findings by Einav et al. (2018) to a setting with competing sellers: As long as buyers do not face auction-specific hassle costs, competing sellers will only offer auctions. But if sellers' valuations are continuously distributed and buyers face auction-specific hassle costs, it is an equilibrium that sellers with low opportunity costs of selling offer auctions while sellers with high opportunity costs offer posted prices.

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 and identical 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 mechanisms chosen by the sellers, buyers act as price takers and the market clears. In other words, buyers who do not trade in equilibrium cannot benefit from trading at a price offered by a seller who does not trade in equilibrium, and buyers who do trade in equilibrium cannot benefit from either not trading or trading with some other seller who does not trade in equilibrium.

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 can therefore be depicted by a set of points in the plane,

[3]Eeckhout and Kircher (2010) demonstrate that for competing sellers 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.

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. Part of the literature (see e.g. Carare and Rothkopf, 2005; Wang et al., 2008; Einav et al., 2018), however, has reasonably emphasized that posted prices may be preferred by at least some buyers due to lower hassle costs that can be attributed to waiting times, the time needed to enter an auction several times (Leszczyc et al., 2009) and the costs of monitoring different auctions when searching for options promising a greater surplus (Chan et al., 2017).[4] Even when some people enjoy taking part in auctions, assuming that hassle costs are, on average, larger compared to posted prices seems reasonable. When taking these auction-specific hassle costs into account, we 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 $(P, R)$–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

[4]Other reasons for why buyers might find auctions less attractive than posted-price sales have been identified e.g. by Harris and Raviv (1981) (excess capacity), Wang (1993) (homogenous buyer valuations), Mathews (2004) and Bauner (2015) (risk aversion), and Zeithammer and Liu (2006) (time discounting).

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. 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 (2017).

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. (2018) 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.

In our context, all items are offered online and each seller has only very few items due to the initial sales mechanism for tickets by UEFA. By contrast, Sun (2008) considers a seller with multiple items that are simultaneously offered with posted prices and in auctions. Comparable to our hassle costs, he adds a disadvantage of auctions due to monitoring costs or the necessity to wait until the auction has closed. He then shows that the two mechanisms serve as a screening device. Kuruzovich and Etzion (2018) consider sellers who utilize online auctions and offline channels with posted prices simultaneously. They then analyze theoretically and empirically how offline demand impacts the characteristics of auctions (reserve price, sales probability and prices). While we compare auctions using optimal start prices with posted prices, Wang (2017) analyzes a seller's choice between auctions with zero start prices and posted prices and finds that a wider dispersion of bidder valuations works in favor of auctions only if the web traffic is sufficiently large. Last, the choice between auctions and posted prices by buyers is considered by Katehakis and Puranam (2012) in the context of sequential purchases of multiple units and Jiang et al. (2013) under the assumption of bounded rationality, but neither of these papers consider the mechanism choice of (competing) sellers.

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.

# 2 Theory

## 2.1 The Model

Consider the following set-up modelling online trade. $s \geq 1$ 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.[5] 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 $\delta \leq \frac{1}{2}$.[6] 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 $i$. The special case of a monopolistic seller (i.e., $s = 1$), resembles the model analyzed in Einav et al. (2018).[7]

## 2.2 Buyer competition

For a given profile $\mathbf{m}$ of sellers' mechanism choices, we assume that buyers are price takers. 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 that accounts for the difference in hassle costs between auctions and posted prices, i.e., $m_{ic} = s_i$ for an auction with start price $s_i$ and $m_{ic} = f_i - c$ for a posted price $f_i$. We will refer to the $|\mathcal{B}|$th lowest value in $(\mathbf{m}_c, \mathbf{v})$ as the market clearing price $p^*$.[8] By construction, there are as many buyers with a valuation $v > p^*$ as sellers with a mechanism $m_c \leq p^*$. To determine trading partners, a (random) one-to-one matching of buyers with valuation $v > p^*$ and sellers with mechanisms $m_c \leq p^*$ is formed. If seller $i$ offers an auction with starting price $s_i \leq p^*$ and is matched with buyer $j$, she receives $p^*$ from $j$, her payoff is $p^* - r_i$, and the buyer's payoff is $v_j - p^*$. If seller $i$ offers a posted price $f_i$ with $f_i - c \leq p^*$ and is matched with buyer

[5] 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.

[6] 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.

[7] In the main text, Einav et al. (2018) analyze a model with a monopolistic seller and identical buyers. A setting with a private value component that is independently distributed across buyers is analyzed in an Online Appendix. Restricting ourselves to $s = 1$ in our model, yields all results derived in Einav et al. (2018).

[8] Results do not rely on this particular rule of defining a market clearing price. Any convex combination of the $|\mathcal{B}|$th lowest and the $(|\mathcal{B}| + 1)$th lowest value leaves the results unaltered.

$j$, she receives $f_i$ from $j$, her payoff is $f_i - r_i$, and the buyer's payoff is $v_j - (f_i - c)$. [9]

**Example 1** *Consider a market with two sellers and three buyers and suppose the sellers have chosen the mechanisms* $m_1 = s_1$ *and* $m_2 = f_2$*. Now order the profile of valuation* $\mathbf{v} = (v_1, v_2, v_3)$ *and the profile of mechanisms* $\mathbf{m}_c = (s_1, f_2 - c)$ *from lowest to highest. Suppose we get* $(s_1, v_1, f_2 - c, v_2, v_3)$*. Then,* $p^*$ *is the 3rd lowest entry on this list, i.e.,* $p^* = f_2 - c$ *and buyer 2 and 3 are trading with seller 1 and 2. The buyer matched with seller 1 (who conducts an auction) pays* $p^* = f_2 - c$*, the buyer matched with seller 2 (who offers a posted price) pays* $f_2$*. As auctions generate hassle costs of* $c$*, both buyers receive the same utility in this case, but seller 1 receives a lower revenue than seller 2. If ordering valuations and mechanisms yields* $(s_1, f_2 - c, v_1, v_2, v_3)$ *instead,* $p^* = v_1$*. Again, buyers 2 and 3 trade with sellers 1 and 2, but seller 1 now receives a revenue of* $p^* = v_1$ *while seller 2 still receives* $f_2$*. For* $f_2 < v_1$*, seller 1 would now receive a larger revenue.*

To relate these trading rules to the literature, observe that if all sellers offer posted prices, our trading rules are identical to a posted offer market (see, e.g., Ketcham et al. (1984)) and if all sellers offer auctions, our trading rules are identical to a sellers' offer double auction. The latter follows Peters and Severinov (2006) who demonstrate that cross-bidding forms an equilibrium which yields homogenous final auction prices identical to those in a sellers' offer double auction if sellers compete by simultaneously choosing reservation prices in auctions. For a mixed setting where sellers offer posted prices and auctions, our trading rules guarantee that the market clears and all buyers act optimally given the sellers' offers: It is better for each buyer who trades to trade at the market clearing price rather than not trading at all or trading at a start price or posted price offered by any seller who does not trade. Likewise, no buyer who does not trade would benefit from trading at the market clearing price.

### 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

[9]So 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.

distributions by $\mu_i = (\mu_{ij})_{j \neq i}$. For a given profile $\mu_i$, 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 $\mu_i$ 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 $\mu_i$, depicts the revenue conditional on selling $R(\mu_i, m_i)$ on the vertical and the selling probability $p(\mu_i, m_i)$ on the horizontal axis as a $(P, R)$–plot. Independent of hassle costs $c \in [0, 1)$, we can state some direct implications of the trading rules we investigate. First, market clearing prices conditional on being above $f_i$ (or $s_i$) are increasing in $f_i$ (or $s_i$), i.e., $(P, R)$–plots for auctions and posted prices are downward-sloping.

**Lemma 1** *(i) Consider seller $i$ with expectations $\mu_i$ 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 $\mu_i$. 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 $(\mathbf{m_c}, \mathbf{v})$. Whenever the $|\mathcal{B}|$th lowest value is at least $s'_i$ $(f'_i - c)$, it is also at least $s_i < s'_i$ $(f_i - c < f'_i - c)$. 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 $(s_i, s'_i)$ $((f_i - c, f'_i - c))$. 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 $\mathbf{v}$ this induces a positive probability of $s_i$ $(f_i)$ to be a market clearing price and implies $R(\mu_i, s_i) < R(\mu_i, s'_i)$ $(R(\mu_i, f_i) < R(\mu_i, f'_i))$. ■

To illustrate the lemma, consider seller 1 in Example 1. Observe that seller 1 indeed sells her unit unless $s_1 > v_2$ and that the price she receives (conditional on selling) is increasing from $f_2 - c$ to $s_1$ as soon as $s_1 > f_2 - c$.

A second general feature of buyer competition in our model (independent of hassle costs $c$) 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.*

**Proof.** Let $\mathbf{m}$ be a profile of mechanisms and $\mathbf{v}$ a profile of valuations and suppose seller $i$ offers an auction with start price $s_i$ while seller $i'$ offers an auction with start price $s_{i'}$. As the market clearing price $p^*$ is the $\mathcal{B}$th-lowest value in $(\mathbf{m_c}, \mathbf{v})$, seller $i$ (seller $i'$) trades if and only if $s_i \leq p^*$ ($s_{i'} \leq p^*$) and - in any case - the price is $p^*$. ■

Suppose, for instance, that seller 2 in Example 1 offers an auction with reservation price $s_2 < v_2$ while everything else stays the same. Then, both auctions trade at the 3rd lowest value in $\mathbf{m_c}$ which is $s_2$ whenever $s_1 < v_1 < s_2 < v_2 < v_3$, whereas it is $v_1$ if $s_1 < s_2 < v_1 < v_2 < v_3$.

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 $s = f$. Consider, for instance, again Example 1 with $s_1 < v_1 < f_2 - c < s_2 < v_2 < v_3$. If $f_2 > v_2$, seller 2 sells the unit at a posted price $f_2$ but not at an auction with start price $f_2$.

**Lemma 3** *Consider seller $i$ with expectations $\mu_i$ 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 $s_i = f_i$. (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 $\mu_i$. 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 whether $i$ offers an auction with start price $s_i$ or a posted 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 posted 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 $f_i$ with $s_i - c$ is the market clearing price, i.e., the unit is sold with a posted price $f_i = s_i$ but not at an auction with a starting price $s_i$. This implies $p(\mu_i, f_i) > p(\mu_i, s_i)$. ■

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 $i$ and sellers will never choose to sell at a posted price.

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,

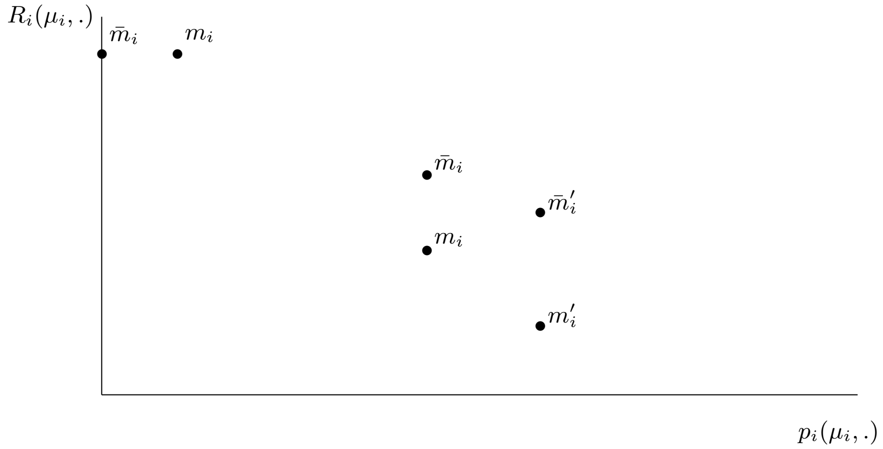


Figure 1: Elements of $(p, R)$–plots for auctions and posted prices with hassle costs.

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 1). 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 1). The intuition is simple: Reducing the posted price by $\delta$ reduces revenue conditional on sale by $\delta$, but reducing the start price of an auction by $\delta$ reduces revenue conditional on sale (by $\delta$) 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.

**Lemma 4** *Suppose $c > 0$ and consider seller $i$ with expectations $\mu_i$. (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 $f_i = c$.*

**Proof.** Let $m_i$ and $\bar{m}_i$ be mechanisms offered by seller $i$ with reservation value $r_i$ and expectations $\mu_i$. (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 1). (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 $f_i$. 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 $\delta$ 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 1). (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 1** *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 4, $(P, R)$–plots of auctions and posted prices for given beliefs cross at most once. For given beliefs $\mu_i$ 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 4 for the entire ordered list of mechanisms. This together with 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. ■

### 2.4 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 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 4 also implies several Hypotheses regarding the relative position of posted prices and auctions in the $(P, R)$–plot (for an illustration see Figure 2). Proposition 1 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.

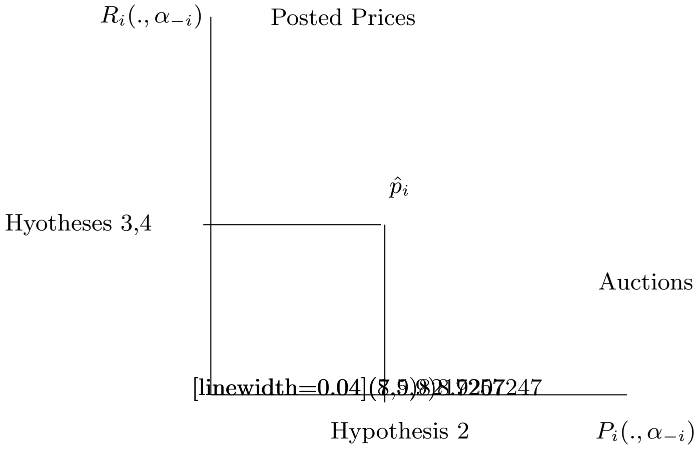


Figure 2: Single-crossing $(p, R)$–plot and Hypotheses 2–4.

**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 1 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 (who 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 are 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. 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 national football associations. Because of excess demand, tickets were distributed in a lottery among the applicants in the end of January 2008.[11] In each match, there were three quality categories of tickets depending on the distance and the angle to the pitch. Original prices differed between qualities and varied form €45 (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.

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

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

eBay provided the main platform for re-sales, and created an own category for the EURO 2008 on their German website. We used the web spider BayWotch to collect data from February 1, 2008. 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).[12] Sellers decided on the selling mode and the posted or an auction's start price, both of which we will refer to as the *start price* in order to save notation. 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.

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. Most offers encompass more than one ticket. Packages with three and more tickets are rare due to the low probability of receiving more than two tickets in the original allocation by the UEFA. As the final price is likely to be affected by the number of competing offers, we control for 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 increase as the match approaches, but starts decreasing at some point as hassle costs for exchanging the tickets in due time become very high. Therefore, we will also control for the square of days left until the start of the match. Finally, the literature has shown that prices may depend on the duration of postings, which sellers could choose to be one, three, five, seven or ten days,[13] and on the weekday and time when an auction ends.[14]

### 3.2 A First Look at Prices and Selling Probabilities

We start by testing Hypotheses 1 and 2, which refer to a separate analysis of auctions and posted prices. 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). In all regressions in Table 2 and thereafter, standard errors are clustered at the match level.

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 account sold items,

[12]Our original data set also 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]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.

[14]For instance, Lucking-Riley et al. (2007, p. 230) argues that bidders are more active in their leisure time.

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 |

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, as 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 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 use the default start price of €1. 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

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 |
| $R^2$ (or Pseudo-$R^2$) | 0.7604 | 0.3194 | 0.6363 | 0.2427 |
| 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.

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*).

Next, we compare auctions and posted prices more formally using the control variables listed in Table 1. 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.

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, and lower when there are more simultaneous auctions for the same match. Model 2 shows that, in line with *Hypothesis 3*, the selling probability is about 40 percentage points higher for auctions, decreasing in the time left to the match and in the number of simultaneously running offers, and increasing in auction duration. Last, Model 3 supports Hypothesis 5 by showing that the selling price is lower for auctions. As for the control variables, selling prices are higher if there are fewer simultaneously running offers, quality is higher and tickets are sold in a bundle.

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.[15] 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

As start prices are considerably higher for posted prices, we disaggregate our comparison of auctions and posted prices by intervals of start prices. 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.

Table 5 is concerned with the impact of the start price on the comparison of final prices in auctions and posted-price offers. The last column repeats model 3 from Table 3 and shows that, when considering the whole data set and without controlling for start prices, auctions sell at lower prices than posted-price offers do. However, when restricting the sample to the different

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

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 |
| $R^2$ (or Pseudo-$R^2$) | 0.5818 | 0.3380 | 0.2323 |
| 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.

categories of start prices introduced in Table 4, the auction dummy is significantly positive for the two intervals with the lowest start prices, but insignificant for all other intervals. In other words, Table 5 shows that our previous result that auctions sell at lower prices than posted-price items 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.

Table 6 reports the results of probit estimations on selling probabilities. For easier reference, model 1 repeats model 2 of Table 3 and shows that auctions are more likely to sell than posted prices when not controlling for the start price. However, when controlling for the logarithm of the start price in model 2 we find the opposite result, that posted prices are more likely to sell than auctions *with a similar start price*. This confirms Hypothesis 6 and is in line with our assumption of lower hassle costs of posted-price transactions for some buyers.

Probit model 2, in which we control for the selling mode, is based on the strong assumption that the impact of all regressors is independent of whether the item is offered in an auction or at a posted price. As we will later need estimates for the impact of the logarithmic start price on selling probabilities, models 3 and 4 of Table 6 estimate this effect within separate regressions for auctions and posted price offers. We will later refer to the notation used in the following formalization of the estimated selling probabilities for the respective subsamples:

$$p_i^A = \Phi\left(\hat{\beta}_0^A + \hat{\beta}_S^A \ln S_i + \hat{\beta}_{\mathbf{x}}^{\mathbf{A}} \mathbf{x_i}\right) = \Phi(\hat{y}_i^A) \quad (1)$$

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

where $\hat{y}_i^k$ denotes the predicted argument of the probability function for the regression based on the data for selling mode $k$. We find that the start price particularly matters for auctions: increasing the logarithm of the relative start price by 1 reduces the selling probability for auctions by 63 percentage points in auctions compared to 24 percentage points with posted prices.

Note carefully that, while (1) and (2) are estimated on the subsamples of either auctions or posted price offers only, the regression results can be used to predict the arguments of the probit functions, $\hat{y}_i^A$ and $\hat{y}_i^F$, for the entire sample. For instance, in the case of an auctioned item, $\hat{y}_i^F$ represents the predicted argument of the probit function in the hypothetical case that this same item would have been offered at a posted price equal to the observed auction start price.

### 3.4 Selling Probabilities and the Ranking of Selling Modes

In our theory, the relationship between expected revenue if 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 unique intersection of $(p, R)$–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 3 indicates that this relationship may also hold empirically: For

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).

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dep. variable | Sold (1 = yes) | Sold (1 = yes) | Sold (1 = yes) | Sold (1 = yes) | *ESP* |
| Selling mode | All | All | Auctions only | Posted Prices only | Auctions only |
| Auction (1=yes) | 0.4091*** | -0.1169*** | | | |
| | (0.0182) | (0.0196) | | | |
| ln Start Price | | -0.5735*** | -0.6258*** | -0.2455*** | -0.4299*** |
| | | (0.0284) | (0.0353) | (0.0411) | (0.0228) |
| Days left to match | -0.0071** | -0.0427** | 0.0400 | -0.0367*** | -0.0307 |
| | (0.0034) | (0.0176) | (0.0299) | (0.0127) | (0.0907) |
| Days left to match squared | 0.0004 | 0.0023* | -0.0036 | 0.0022** | -0.0024 |
| | (0.0003) | (0.0012) | (0.0023) | (0.0009) | (0.0069) |
| Number of competing offers | -0.0002*** | -0.0016*** | -0.0004 | -0.0010*** | -0.0039*** |
| | (0.0001) | (0.0003) | (0.0002) | (0.0003) | (0.0012) |
| *End of auction (dummies)* | | | | | |
| Saturday | -0.0095 | -0.0207 | 0.0152 | -0.0222 | 0.1329** |
| | (0.0062) | (0.0237) | (0.0281) | (0.0179) | (0.0624) |
| Sunday | -0.0102** | -0.0588** | -0.0194 | -0.0480** | -0.0465* |
| | (0.0041) | (0.0240) | (0.0268) | (0.0241) | (0.0267) |
| Evening (6 to 10pm) (d) | 0.0022 | -0.0379*** | -0.0577** | -0.0069 | -0.0901*** |
| | (0.0046) | (0.0129) | (0.0250) | (0.0068) | (0.0289) |
| *Ticket quality (base: top quality)* | | | | | |
| Medium quality | -0.0078 | 0.1036*** | 0.0454 | 0.0575*** | 0.6557*** |
| | (0.0081) | (0.0306) | (0.0431) | (0.0173) | (0.1012) |
| Regular seats | -0.0041 | 0.2645*** | 0.2870*** | 0.1108*** | 2.9657*** |
| | (0.0036) | (0.0246) | (0.0326) | (0.0184) | (0.1658) |
| *Number of offered tickets (base: 1)* | | | | | |
| 2 tickets | 0.0058 | 0.1098*** | 0.0633 | 0.0551*** | 0.3048** |
| | (0.0052) | (0.0307) | (0.0552) | (0.0176) | (0.1375) |
| 3 or more tickets | -0.0086 | 0.0586*** | 0.0415 | 0.0322*** | -0.0492 |
| | (0.0067) | (0.0215) | (0.0515) | (0.0107) | (0.1546) |
| *Duration of posting (base: 3 days)* | | | | | |
| 5 days | 0.0166** | 0.0625** | 0.0837** | 0.0210** | 0.2989*** |
| | (0.0066) | (0.0263) | (0.0366) | (0.0099) | (0.0922) |
| 7 days | 0.0206*** | 0.0974*** | 0.1009*** | 0.0306*** | 0.3713*** |
| | (0.0059) | (0.0267) | (0.0345) | (0.0110) | (0.0947) |
| 10 days | 0.0159** | 0.1000*** | 0.0562 | 0.0508*** | 0.4244*** |
| | (0.0080) | (0.0304) | (0.0488) | (0.0147) | (0.0851) |
| Match Dummies | Yes | Yes | Yes | Yes | Yes |
| $R^2$ (or Pseudo-$R^2$) | 0.3380 | 0.6774 | 0.7604 | 0.3194 | 0.6418 |
| Observations | 12,315 | 12,315 | 10,565 | 1,600 | 10,259 |

For the Probit estimations (models (1) – (4)), the table displays marginal effects calculated at $\ln S_i = 1$ and at the mean of all other variables. Estimation of model (5) is OLS. Robust standard errors, clustered at match level, in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

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 3 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 3 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 obtain such a prediction, 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.

As a first step, we use the estimates from model 3 of Table 6, which only includes auctioned items, to predict the argument $\hat{y}_i^A$ of the probability function in (1), and the estimates from model 4 of Table 6 to predict the corresponding argument $\hat{y}_i^F$ of the probability function in (2) for posted-price offers. Recall that, if $i$ is an auctioned item, $\hat{y}_i^F$ is the predicted argument of the probit function based on the estimates of model 4 in the hypothetical case in which $i$ had been offered at a posted price equal to the actual auction's starting price $S_i$ in our data.

Next, we calculate the hypothetical posted price $F_i'$ at which an auctioned item would have had to be offered in order to sell with the same probability by equating the right-hand sides of (1) and (2) and substituting for $S_i = F_i$ in (2):

$$
\begin{aligned}
F_i &= e^{(\hat{\beta}_0^A + \hat{\beta}_S^A \ln S_i + \hat{\beta}_{\mathbf{x}}^{\mathbf{A}} \mathbf{x_i} - \hat{\beta}_0^F - \hat{\beta}_{\mathbf{x}}^{\mathbf{F}} \mathbf{x_i})/\hat{\beta}_S^F} = e^{(\hat{y}_i^A - \hat{\beta}_0^F - \hat{\beta}_{\mathbf{x}}^{\mathbf{F}} \mathbf{x_i})/\hat{\beta}_S^F} \\
&= e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F}
\end{aligned}
$$

The second and third equations are true since $\hat{y}_i^A$ and $\hat{y}_i^F$ are the predictions based on the actual auction's starting price. If $R_i$ denotes the selling price of the auction, the excess selling price $ESP_i$ of auction $i$ over a hypothetical posted-price offer with the same selling probability is

$$ESP_i = R_i - F_i = R_i - e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F}. \quad (3)$$

Model 5 of Table 6 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*, this regression includes only sold items, so that we use OLS to estimate the model, and the number of observations is reduced to $n = 10,259$. The significantly negative coefficient of the logarithmic start price shows that 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.[16]

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 model 5 of Table 6 confirms the single crossing result from the theoretical model. Another way of illustrating this is to directly look at $(p, R)$–plots generated by our data.

For instance, suppose that selling probabilities for auctions and posted prices are given by equations (1) and (2), respectively. Then, the $(p, R)$–plot for posted prices is immediately given by the inverse of (2), 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:[17]

$$R_i = \hat{\alpha}_0 + \hat{\alpha}_S S_i + \hat{\alpha}_{\mathbf{x}} \mathbf{x_i}. \tag{4}$$

Solving (4) for $S_i$ and substituting for $S_i$ in (1) yields the inverse of the $(p, R)$–plot for auctions. Figure 4 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 is confirmed as the $(p, R)$–plot for auctions cuts that for posted prices from below.

# 4 Concluding Remarks

Our model of competing sellers' choices of mechanism confirms the superiority of auctions in the absence of hassle costs and demonstrates the single-crossing of optimal mechanisms in the presence of hassle costs. We derive these results theoretically by assuming that competing auctions retrieve market clearing prices, which has been shown to emerge as an equilibrium of cross-bidding between auctions by Peters and Severinov (2006). In this sense, our model gives a "better shot" at auctions than the literature that assumes a commitment to a particular mechanism of a particular seller either before or after buyers learn their valuation (see McAfee

[16] 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 available upon request.

[17] The result of this estimation was given in Table 2 above.


Figure 3: Predicted selling probabilities and final prices conditional on sale for auctions and posted prices.

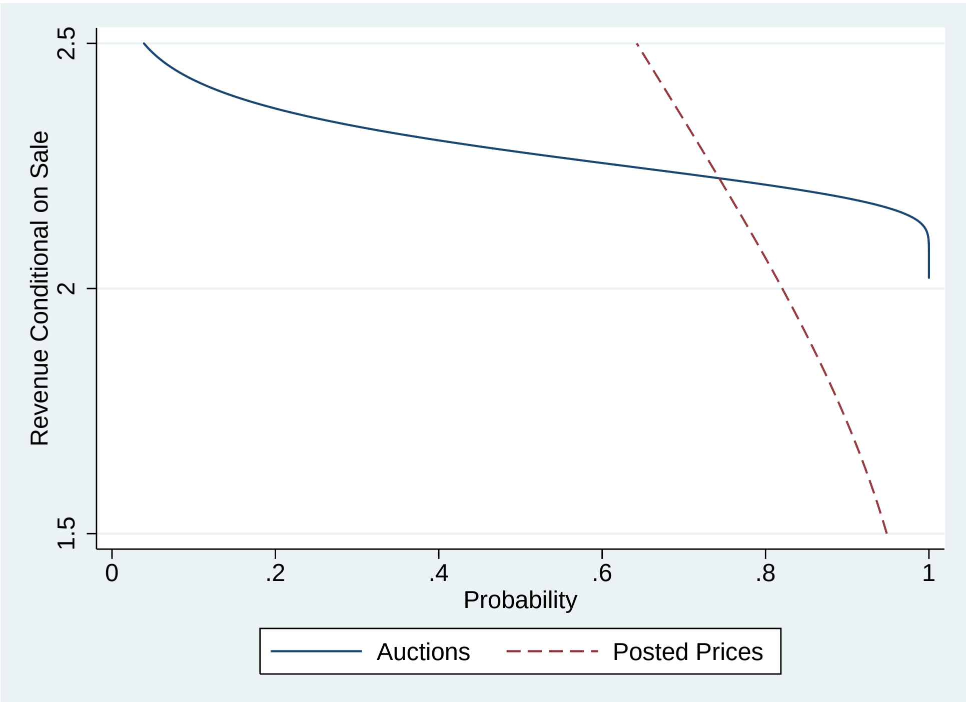


Figure 4: A $(p, R)$-plot derived from observed bidder behavior.

(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 mentioned in the introduction, the same outcome emerges in 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 $f$. Introducing hassle costs for auctions would also lead to an increasing benefit of posted prices for sellers with higher valuations 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 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. From an applied perspective, this suggests that, given the selling probability a seller wants to implement, she should either hold an auction with the optimal reserve price or choose the posted price that is sold with the desired probability. While determining the optimal start price requires a sound understanding of the market and the distribution the buyers' and other sellers' valuations are drawn from, this result also proves useful as rule of thumb: sellers should offer their item in an auction if and only if they put sufficiently high emphasis on the selling probability compared to the revenue in case of sale.

To see the value added of our empirical strategy, recall that the literature reports 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. The empirical strategy follows the model which identifies the selling mode that maximizes a seller's revenues for her individually optimal selling probability, depending on her reservation value.

Let us add some methodological remarks concerning the link between our model and the empirical analysis. In our model, the reservation values determine uniquely the sellers' 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 it is reservation values that drive the mechanism choice. All we can say is that our empirical results strongly confirm the hypotheses derived from the theory. However, other papers using inventories as proxies for reservation values (Hammond, 2010) do argue that self selection is driven by reservation values, so that our theory helps understand this empirical result.

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, so that unobserved heterogeneity of reservation values is no concern for our empirical strategy. However, 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.* Indeed, we cannot rule out that posted-price sellers would choose different durations or end dates when using an auction. If the sellers' attributes which determine these other choices 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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