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Competing Trade Mechanisms and Monotone Mechanism Choice*

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Abstract

We analyze mechanism choices of competing sellers with private valuations and show the existence of monotone pure strategy equilibria where sellers with higher reservation value choose mechanisms with a lower selling probability and a larger revenue in case of trade. As an application we investigate the choice between posted prices and auctions and demonstrate that sellers refuse to offer posted prices as long as (risk-neutral) buyers do not differ with respect to their transaction costs in both trade institutions. If some buyers have lower transaction costs when trading at a posted price, it is optimal for sellers to offer posted prices if and only if they have a sufficiently high reservation value. We develop an empirical strategy to compare revenues of posted prices and auctions that takes selling probabilities explicitly into account, and confirm our theoretical predictions with data from eBay auctions on ticket sales for the EURO 2008 European Football Championship.

JEL Codes: D43, D44, D82, L13.

Keywords: Competing Sellers, Single-Crossing, Auctions, Fixed Prices.

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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, 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] Design recommendations by trading platforms or user-groups[2] typically share the following three insights: First, the higher the reserve price in an auction or the posted price, the lower is the probability that the good will be sold. Thus, high start prices[3] should only be considered if one cares about the trading price rather than the probability of trade. Second, while auctions are superior when the uncertainty on the potential buyers' valuations is high, posted prices are recommended when a standardized product with a clear-cut reference price is offered. Third, if a seller highly values the good herself, she may offer a high posted price hoping for the "lucky punch" to meet someone with an even higher willingness to pay.

All these recommendations read as if they were directly taken from the standard textbook treatment based on the seminal work by Myerson (1981) on monopolistic mechanism design, i.e. optimal mechanism design for a *given* set of buyers: First, the trade-off between selling probabilities and revenues follows from individual rationality as only the high- valuation buyers participate when reserve prices or posted prices are high. Second, incentive compatibility requires that buyers with a high valuation bid more aggressively in auctions, and this allows for higher revenues due to price discrimination. This advantage of auctions as compared to posted prices, however, decreases when buyers do not differ much in their valuations, and posted prices may then be optimal due to reduced uncertainty, immediate transactions, or other perceived virtues of posted prices.[4] Third, the advantage of auctions over posted prices is lower for sellers with high valuations since price discrimination becomes more relevant as the number of buyers with a valuation above the reserve price gets large.

[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, the user guide to eBay on http://ebay.about.com/ by Aron Hsiao.

[3] Throughout, we will use the general term "start price" both for reserve prices in auctions and posted (or fixed) prices. In the latter case, start prices are identical to selling prices in case of a trade.

[4] See Wang (1993) for a theoretical treatment of monopolistic sellers and e.g. Mathews (2004) who demonstrate a superiority of posted prices over auctions due to risk aversion or Zeithammer and Liu (2006) who emphasize the impact of time discounting.

But while Myerson (1981) and the vast majority of the literature on optimal selling strategies (see the literature review below) assume a monopolistic seller, the usual online seller faces considerable competition by other providers of identical or similar products. We develop a theoretical model to demonstrate that the aforementioned trade-off between the selling probability and the revenue in case of trade is not only a feature of monopolistic mechanism design, but also ensures the existence of monotone pure strategy equilibria when sellers compete. In such an equilibrium, sellers with high reservation values choose mechanisms with a lower selling probability and a higher revenue in case of trade. We apply this model to the choice between posted prices and auctions with reserve prices and use data from secondary ticket sales for the 2008 UEFA European Football (Soccer) Championship in Austria and Switzerland on German eBay (EURO 2008) to illustrate its explanatory power for real-life mechanism design. Specifically, we demonstrate that, in line with our theoretical prediction, auctions outperform posted prices if and only if the (induced) selling probability is high, i.e. if reserve prices are lower.

We model the strategic choice of a trade mechanism 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. Sellers are endowed with one unit of the homogenous good and choose a trade institution. For a given strategy of mechanism choice by the other sellers, any mechanism is – for the purpose of optimal mechanism choice – fully characterized by the associated 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 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. Mechanisms that are undominated in this way can therefore be ordered according to their selling probability, and a seller's mechanism choice satisfies *single-crossing of incremental returns* as defined in Milgrom and Shannon (1994): If a mechanism with a lower selling probability is better for a seller with a certain valuation as compared to a mechanism with a higher selling probability, it is also better for any seller with a higher valuation. If neither the set of undominated mechanisms nor the ordering of these mechanisms according to the selling probability depends on the (anticipated) strategy profile of other sellers, Theorem 1 in Athey (2001) implies the existence of a monotone equilibrium where sellers with higher types choose mechanisms with lower selling probability.

We apply these findings to sellers' choices between posted prices and auctions. We follow Peters and Severinov (2006) by assuming that buyers cross-bid such that auctions determine market clearing prices (for the reserve prices set by sellers). We first demonstrate that, when buyers care only about the price of a transaction and traders do not differ too much with respect to their expectations for market clearing prices, then there are no mutually beneficial posted prices that sellers are willing to offer and buyers are willing to accept. In this case, posted prices are dominated mechanisms and sellers will only offer auctions with reserve prices that are monotone increasing in their valuation. Part of the literature, however, has reasonably emphasized that posted prices may be preferred by at least some buyers due to lower transaction costs, impatience or risk aversion (see e.g. Bauner (2015)). We restrict attention to transaction costs that are lower for posted prices. 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 (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 implies that selling probabilities for posted prices are lower than selling probabilities for auctions, whereas successfully posted prices are above final auction prices. In line with the previous literature (see below), we confirm these hypotheses with our data for tickets to matches of the 2008 UEFA European Football Championship.

But our model does not only allow to draw conclusions regarding the aggregate performance of posted prices and auctions. If (P, R)–plots of posted prices and auctions indeed satisfy single-crossing, there should be 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. To test this hypothesis, we first develop an empirical strategy for estimating 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.

The remainder of the paper is organized as follows: After relating to the literature, we present our general model on the choice of mechanisms in section 3. Section 4 turns more specifically to auctions vs. posted prices and derives our empirically testable hypotheses. Section 5 presents our empirical analysis. We conclude in section 6.

2 Relation to the Literature

Our analysis regarding the existence of monotone pure strategy equilibria adds to the literature on competing mechanism designers that establishes the optimality of auctions and addresses the convergence of optimal reserve prices to the sellers' costs in a competitive equilibrium setting (see McAfee (1993) or Peters (1997)) or for a restricted set of mechanisms (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 exemption see Peters (1997)). In 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]

Our specific model for the comparison of posted prices and auctions in section 4 first offers a simple and tractable environment to establish the superiority of auctions in the absence of transaction costs as also demonstrated in the competitive settings of McAfee (1993) or Peters (1997).[6] When some buyers have higher transaction costs for auctions, however, we derive an equilibrium where sellers with high reservation values prefer posted

[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).

[6]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.

prices, and where posted prices yield higher selling prices than auctions for identical selling probabilities if and only if those probabilities are low.

Our findings for the coexistence of posted prices and auctions are most closely related to Hammond (2010), Hammond (2013) and Bauner (2015). Hammond (2010) confirms empirically theoretical arguments by Harris and Raviv (1981) that sellers with large (small) inventories tend to chose posted prices (auctions). This result is driven by the fact that the advantage of auctions over posted prices increases when the number of potential buyers per item is large. In Hammond (2013), the coexistence of posted prices and auctions emerges due to the fact that sellers prefer to be in market with fewer rivals; see also Ellison and Fudenberg (2003). This differs from our model that does not require that buyers pick a specific auction but allows for cross-bidding as in Peters (1997). As in our model, sellers with high outside options self-select to posted prices, and hence accept a lower selling probability in exchange for a higher revenue in case of sale.

As in McAfee (1993), buyers in Hammond (2013) learn their valuations before they self-select to a mechanism. This is different in Bauner (2015) where buyers learn their valuation after their choice of a mechanism. By contrast to our setting, there is no cross-bidding, and buy-it-now options are considered instead of posted prices. Bauner (2015) then focuses on the empirical analysis of ticket sales of Major League Baseball tickets on eBay for home games of the Cincinnati Reds in the 2007 regular season. He also identifies the sellers' outside options as a crucial factor for their mechanism choice.[7]

The predictions of the model regarding the aggregate performance of auctions and posted prices has been confirmed by the empirical literature: posted prices sell less often, but yield higher revenues in case of trade (see Halcoussis and Mathews (2007) for a study on concert tickets and Hammond (2010) for compact discs.[8] While this revenue-probability trade-off is an interesting observation, it cannot answer the question which sales mode leads to higher payoffs in case the selling probability induced by either posted prices or reserve prices is the same. Our main empirical contribution is to close this gap

[7]In a purely theoretical paper, Anwar and Zheng (2015) also consider the coexistence of buy-it-now options with auctions. In their model, random matching of buyers to sellers in auctions may lead to allocative inefficiencies in case cross-bidding among auctions is imperfect, for instance due to late bidding (sniping). They then show that these inefficiencies are mitigated if some high-valuation buyers self-select to buy-it-now options, which also increases the expected revenue of sellers.

[8]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.

by identifying posted prices and reserve prices that yield identical selling probabilities, and then compare the revenues for a those induced selling probabilities. We find that auctions are superior if and only if the selling probabilities are high. This identification technique allows to compare the relative performance of auctions and posted prices (i.e. their position in the (P, R)–plot) without requiring structural estimations as in Hammond (2013), and without the need to observe experiments by (possibly price-discriminating) sellers who sell the same commodity multiple times as in Einav et al. (2013).

3 Competing Trade Mechanisms

3.1 A Finite Action Game with Incomplete Information

In this section, we analyze a game of mechanism choice by players who, based on the anticipated strategy profile of other players, form expectations regarding the probability that a given mechanism is accepted and the expected payoff in case of acceptance. Throughout this section, we do not model the behavior of individuals who participate in the mechanisms offered by the players. All we need for the analysis is the acceptance probability of a mechanism and its expected return for a given profile of mechanisms chosen by the other players. For the particular example in Section 4 we will also describe how these features of a mechanism emerge from the participants' (i.e. buyers') behavior.

Consider the following game with $s \geq 2$ players: Player $i \in \mathcal{S} \equiv \{1, ..., s\}$ observes her own type $t_i \in \mathcal{T}_i = [\underline{t}_i, \bar{t}_i] \subset \mathbb{R}$ and chooses a *mechanism* $m_i \in \mathcal{M}_i$ where $\mathcal{M}_i$ is a finite set. Let $\mathbf{t} = (t_1, \ldots, t_s)$ be a profile of types and $\mathbf{m} = (m_1, \ldots, m_s)$ a profile of mechanisms. A pure strategy α_i of player i specifies a mechanism choice for every type, i.e., $\alpha_i : \mathcal{T}_i \to \mathcal{M}_i$. Let $\mathcal{T} = \mathcal{T}_1 \times \ldots \times \mathcal{T}_s$, $\mathcal{M} = \mathcal{M}_1 \times \ldots \times \mathcal{M}_s$, and $\alpha = (\alpha_1, \ldots, \alpha_s)$. The type of player i is distributed with a continuous density $h_i(t_i)$ with full support, and types are private information in the sense that players only know their own type and the distributions of other types.[9] Player i's payoff function is $u_i : \mathcal{M} \times \mathcal{T}_i \to \mathbb{R}$.

Mechanisms We describe a mechanism by the probability with which the mechanism is accepted and the expected revenue that is generated in case of acceptance. For a profile of chosen mechanisms $\mathbf{m}$, player i's mechanism is *accepted* with probability $q_i(\mathbf{m}) \in [0, 1]$ and is rejected with probability $1 - q_i(\mathbf{m})$. If player i anticipates strategies $\alpha_{-i} = \alpha \backslash \alpha_i$

[9]We will discuss the extension towards a joint density of types – i.e. interdependent valuations – at the end of this section.

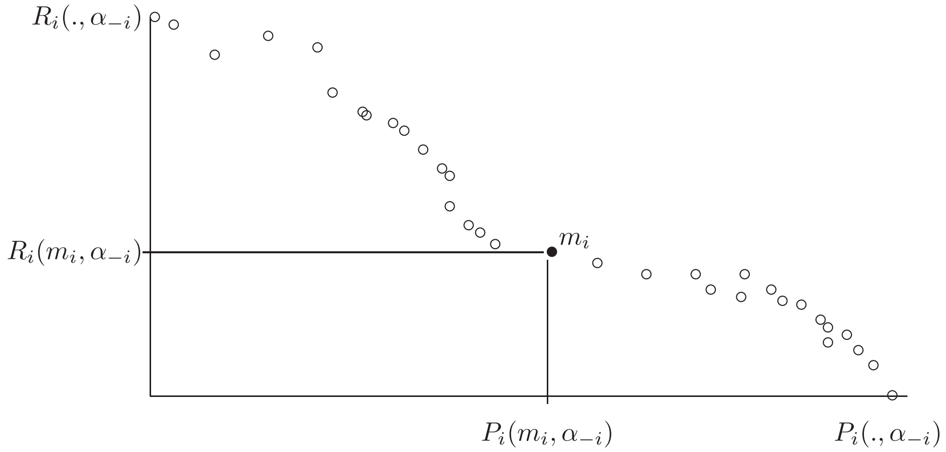

Figure 1: An example of a (P, R)–plot $\mathcal{PR}(\alpha_{-i})$ of player i who anticipates strategies α_{-i}.

by the other players, we denote the probability that player i assigns to the event that mechanism m_i is accepted by $P_i(m_i, \alpha_{-i})$. If the mechanism is rejected, player i enjoys a (reservation) utility $r_i(t_i)$ where r_i is a strictly monotone increasing function of t_i. If the mechanism is accepted, player i's expected revenue will be denoted by $R_i(m_i, \alpha_{-i})$.

$(\mathbf{P}, \mathbf{R})$–plots To represent player i's expectations regarding the choice of different mechanisms, we plot the expected return in case of acceptance for player i (of type t_i) when choosing mechanism m_i and anticipating strategies α_{-i}, $R_i(m_i, \alpha_{-i})$, against the expected probability of acceptance $P_i(m_i, \alpha_{-i})$.[10] Note that a point in this plot fully captures player i's expected payoff

$$P_i(m_i, \alpha_{-i})R_i(m_i, \alpha_{-i}) + (1 - P_i(m_i, \alpha_{-i}))\, r_i(t_i)$$

from offering mechanism m_i when she expects the other players to play strategies α_{-i}. Formally, for player i who expects the other players to play the profile α_{-i}, a (P, R)–plot is a set

$$\mathcal{PR}(\alpha_{-i}) = \{(P_i(m_i, \alpha_{-i}), R_i(m_i, \alpha_{-i})) \mid m_i \in \mathcal{M}_i\}.$$

Observe that – for private valuations – the (P, R)–plot does not depend on the players type t_i but only on the strategy profile α_{-i} she anticipates.

Applications This set-up captures a variety of situations where players compete with the mechanisms they choose and the profile of chosen mechanisms determines when a player's mechanism is accepted and what the expected return in case of acceptance will

[10] See Figure 1 for an illustration. If expectations are simply based on past observations, (P, R)–plots coincide with the demand plots in Einav et al. (2013).

be. Consider, for instance, sellers who choose a trade institution such as a certain posted price or an auction of a particular format with certain reserve prices or buy-it-now options etc. The profile of competing mechanisms then determines the probability with which a particular seller manages to sell the good and what her expected revenue will be. In general, a mechanism m_i at player i's disposal can thereby capture various aspects of the corresponding interaction between player i and agents who participate in mechanism m_i. Next to m_i being a mapping from the set of participants (and their reported valuations) to the set of allocations and payments (as in the classical literature on mechanism design), m_i can also capture the point in time when the mechanism is offered or characteristics of a mechanism that may induce behavioral biases such as anchoring or an endowment effect.

As an illustration and for further reference, let us introduce the following two examples.

Example 1 (Competing posted prices) *A mechanism m_i offered by player i (i.e. a seller) is the offer to purchase the good of player i at a price f_i. Agents (i.e. potential buyers) apply or try to purchase at a subset of sellers and the good is sold at price f_i to a randomly chosen buyer among those who are willing to purchase. For other players' strategies α_{-i}, $P_i(m_i, \alpha_{-i})$ therefore depicts the probability that at least one buyer selects seller i who offers posted price f_i as indicated by mechanism m_i and the corresponding revenue $R_i(m_i, \alpha_{-i})$ is f_i.*

Example 2 (Competing auctions) *Assume that a mechanism m_i is an auction with a reserve price s_i and suppose that – as in the Perfect Bayesian Equilibrium discussed in Peters and Severinov (2006) – bidders cross-bid until a market clearing price is reached. Then, $P_i(m_i, \alpha_{-i})$ is the probability that the market clearing price is above reserve price s_i as indicated by mechanism m_i and $R_i(m_i, \alpha_{-i})$ is the expected market clearing price (conditional on being at least s_i) if seller i expects the other sellers to choose reserve prices according to strategy profile α_{-i}.*

3.2 Equilibrium Analysis

Dominated mechanisms Consider a (P, R)–plot $\mathcal{PR}(\alpha_{-i})$ for player i who expects the other players to play strategies α_{-i}. We call a mechanism *dominated for player i who expects strategies α_{-i}* if there is another mechanism m_i' that yields a strictly higher expected utility with a probability of acceptance that is not below the corresponding

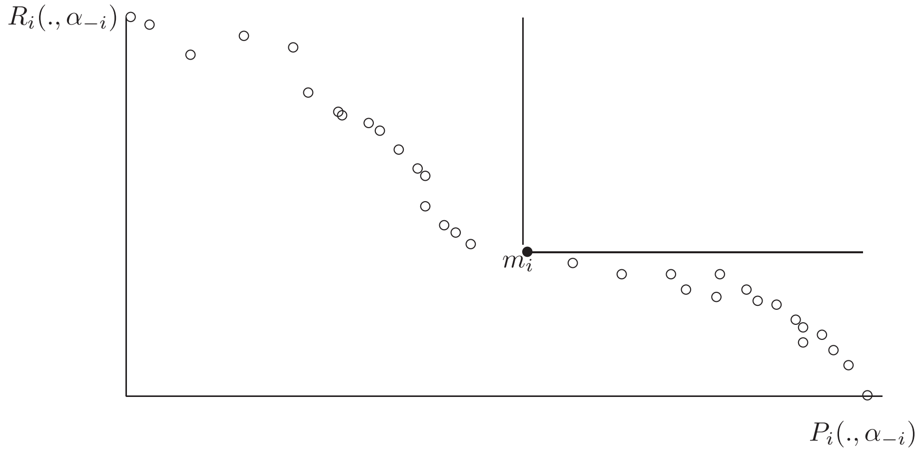

Figure 2: An undominated mechanism $m_i \in \mathcal{PR}(\alpha_{-i})$.

acceptance probability for m_i and an expected return in case of acceptance that is not below the corresponding expected return for m_i.[11] Formally,

Definition 1 *A mechanism* $m_i \in \mathcal{M}_i$ *is* ***dominated in*** $\mathcal{PR}(\alpha_{-i})$ *if there is a mechanism* $m'_i \in \mathcal{M}_i$ *with* $P_i(m_i, \alpha_{-i}) \leq P_i(m'_i, \alpha_{-i})$ *and* $R_i(m_i, \alpha_{-i})) \leq R_i(m'_i, \alpha_{-i}))$ *with one of the two inequalities being strict.*

Graphically, a mechanism m_i is dominated in $\mathcal{PR}(\alpha_{-i})$ if there is a mechanism m'_i in $\mathcal{PR}(\alpha_{-i})$ that does not coincide with m_i and is weakly above and weakly to the right of m_i. We denote the set of mechanisms that are dominated in $\mathcal{PR}(\alpha_{-i})$ by $\mathcal{PR}_d(\alpha_{-i})$ and the complement (i.e. the set of mechanisms that are not dominated or undominated in $\mathcal{PR}(\alpha_{-i})$) by $\mathcal{PR}_u(\alpha_{-i})$ (see Figure 2).

Note that – as the (P, R)–plot – the set of dominated mechanisms may differ across beliefs over actions of other players. However, as types are drawn independently, the plot and the set of undominated mechanisms does not depend on player i's type. This implies the following result.

Lemma 1 *Player* i *who expects* α_{-i} *will always choose a mechanism in* $\mathcal{PR}_u(\alpha_{-i})$.

Example 3 (Auction vs posted prices) *Suppose players are sellers of one unit of a homogenous good and the set of mechanisms* $\mathcal{M}_i$ *for each player* i *is comprised of posted price offers* f_i *and Vickrey auctions with reserve price* s_i. *Let posted prices and reserve*

[11] Note that our notion of dominance refers to returns in case of acceptance and acceptance probabilities for a *given* strategy profile of all other players. Hence, a dominated mechanisms does not resemble a dominated strategy in the usual game theoretic sense. We opted for the term "dominated" because of the graphical similarity to the notion of a dominated portfolio in portfolio choice.

prices be taken from the same finite set on $[0, 1]$ and suppose that buyers and sellers have private valuations for the good that are drawn from a continuous density $g(.)$ on $[0, 1]$. Now let each buyer j with valuation v_j randomly pick one mechanism m_i for which $v_j > f_i$ or $v_j > s_i$ – and apply for the corresponding posted price transaction or submit their valuation as a bid in the auction. Then, a posted price f_i is dominated by an auction with reserve price $s_i = f_i$ because both mechanisms have the same probability of acceptance (as buyers randomize and accept a posted price or start bidding at an auction whenever their valuation is at least f_i) and whenever there is more than one buyer accepting or bidding (which happens with a positive probability) the auction yields a strictly larger revenue.[12]

Monotone mechanism choices If player i anticipates profile α_{-i}, the undominated mechanisms can be ordered according to their probability of acceptance. I.e., for player i and profile α_{-i} mechanisms in $\mathcal{PR}_u(\alpha_{-i}) = \{m^1, m^2, \ldots\}$ can be ordered in such a way that $P_i(m^k, \alpha_{-i}) \leq P_i(m^{k+1}, \alpha_{-i})$. In what follows we restrict attention to sets of mechanisms where the set of undominated mechanisms and the ordering according to the probability of acceptance is independent of the anticipated strategy profile α_{-i}.

Definition 2 *A set of mechanisms is invariant if $\mathcal{PR}(\alpha_{-i}) = \{m^1, m^2, \ldots\}$ is independent of α_{-i} and $P_i(m^k, \alpha_{-i}) \leq P_i(m^{k+1}, \alpha_{-i})$ independent of α_{-i}.*

Observe that Examples 1-3 exhibit invariant sets of mechanisms. If the set of mechanisms is invariant, we can define a monotone strategy as follows.

Definition 3 *Let $\mathcal{M}$ be invariant. A monotone strategy α_i of player i is a mapping $\alpha_i : \mathcal{T}_i \to \mathcal{M}_i$ such that for all $t > t'$ and α_{-i}: $P_i(\alpha_i(t), \alpha_{-i}) \leq P_i(\alpha_i(t'), \alpha_{-i})$.*

Suppose for instance that in Example 1, higher posted prices are less likely to be accepted. Then, a monotone strategy assigns higher posted prices to higher types. Likewise, a monotone strategy in Examples 2 and 3 would be a strategy that assigns higher reserve prices to higher types.

Monotone equilibria The following theorem indicates that the invariance of the set of mechanisms guarantees the existence of an equilibrium in monotone strategies.

[12]The dominance of auctions for a seller who anticipates other sellers to conduct auctions (with reserve prices equal to the sellers valuation) also follows from the results in McAfee (1993) and Peters (1997) who analyze competitive mechanism choice.

Theorem 1 *Let $\mathcal{M}$ be invariant. There is a pure strategy Nash equilibrium where each player i's equilibrium strategy α_i^* is monotone.*

Proof. According to Athey (2001, Theorem 1), there is a pure strategy Nash equilibrium in a finite action game with incomplete information whenever the *single-crossing condition for games with incomplete information* (SCC) (Athey (2001, Definition 3)) is satisfied. To translate this single-crossing condition into our framework, take a complete order $\succeq_i$ over each player i's action space $\mathcal{M}_i$, i.e. for any two mechanisms $m, m' \in \mathcal{M}_i$ either $m \succeq_i m'$ or $m' \succeq_i m$ (or both). For player i, a function $h : \mathcal{M}_i \times \mathcal{T}_i \to \mathbb{R}$ satisfies the (Milgrom-Shannon) *single-crossing property of incremental returns* (SCP-IR) in (m_i, t_i) if, for all $m^H, m^L \in \mathcal{M}_i$ with $m^H \succeq_i m^L$ and all $t^H, t^L \in \mathcal{T}_i$ with $t^H > t^L$: $h(m^H, t^L) - h(m^L, t^L) \geq (>)0$ implies $h(m^H, t^H) - h(m^L, t^H) \geq (>)0$. For a given order $\succeq_i$, a pure strategy of player i, $\alpha_i : \mathcal{T}_j \to \mathcal{M}_j$ is called monotone (or, non-decreasing) if for $t > t'$, $\alpha_i(t) \succeq_i \alpha_i(t')$. The game satisfies SCC for a given order $\succeq$ if for each $i \in \mathcal{S}$: Whenever every other player $j \neq i$ uses a strategy $\alpha_j : \mathcal{T}_j \to \mathcal{M}_j$ that is monotone, player i's objective function, $U_i(m_i, t_i; \alpha_{-i})$ satisfies single crossing of incremental returns (SCP-IR) in (m_i, t_i).

To prove the Theorem, we will demonstrate that our game satisfies SCC whenever mechanisms are invariant and can thus be ordered according to their acceptance probability. By Lemma 1 we know that player i when anticipating strategy α_{-i} will never choose a mechanism $m_i \in \mathcal{PR}_d(\alpha_{-i})$. To establish SCC it therefore suffices to order mechanisms in $\mathcal{PR}_u(\alpha_{-i})$. As M is invariant, $PR_u(\alpha_{-i})$ does not depend on α_{-i}. Now order mechanisms in $PR_u(\alpha_{-i})$ according to their acceptance probability: For $m, m' \in PR_u(\alpha_{-i})$, $m \succeq_i m'$ whenever $P_i(m, \alpha_{-i}) \leq P_i(m', \alpha_{-i})$, i.e. mechanisms with a higher "rank" have a lower probability of acceptance (and a higher expected return). As M is invariant, this ordering does not depend on α_{-i}.

Anticipating the profile α_{-i}, player i (with type t_i) expects

$$P_i(m_i, \alpha_{-i})R_i(m_i, \alpha_{-i}) + (1 - P_i(m_i, \alpha_{-i}))r_i(t_i)$$

from choosing m_i. Now consider any two mechanisms $m^H, m^L \in \mathcal{PR}_u(\alpha_{-i})_i$ and suppose that $P_i(m^H, \alpha_{-i}) \leq P_i(m^L, \alpha_{-i})$. As both mechanisms are undominated in $\mathcal{PR}(\alpha_{-i})$, $P_i(m^H, \alpha_{-i}) \leq P_i(m^L, \alpha_{-i})$ implies $R_i(m^H, \alpha_{-i}) \geq R_i(m^L, \alpha_{-i})$. Now suppose that m^H yields weakly higher returns than m^L if player i is of type t^L, i.e.

$$P_i(m^H, \alpha_{-i})R_i(m^H, \alpha_{-i}) + (1 - P_i(m^H, \alpha_{-i}))r(t^L)$$

$$\geq P_i(m^L, \alpha_{-i})R_i(m^L, \alpha_{-i}) + (1 - P_i(m^L, \alpha_{-i}))r(t^L).$$

Then,

$$P_i(m^H, \alpha_{-i})R_i(m^H, \alpha_{-i}) + (1 - P_i(m^H, \alpha_{-i}))r(t^H)$$
$$\geq P_i(m^L, \alpha_{-i})R_i(m^L, \alpha_{-i}) + (1 - P_i(m^L, \alpha_{-i}))r(t^H)$$

for any $t^H > t^L$ because $r(t^H) > r(t^L)$. The same holds for strict inequalities. This implies SCR-IR for any (m_i, t_i) and thereby satisfies SCC for any player i and profile α_{-i}. With Athey (2001, Theorem 1) our Theorem follows as we consider finitely many actions (or mechanisms) and independently drawn types.[13] ■

According to Theorem 1, there is always an equilibrium in pure strategies where every player chooses a mechanism with (weakly) lower acceptance probability and (weakly) higher returns in case of acceptance as the player's type (or reservation value) increases. Graphically, players move down the set of undominated mechanisms in the (P, R)–plot that belongs to the equilibrium profile α^*_{-i} as their type gets smaller. The higher a players type (and reservation value) the more willing she is to sacrifice selling probability in exchange for higher revenues in case of selling. This simple and intuitive trade-off that shapes the set of undominated mechanisms therefore *ensures* single-crossing and thereby the existence of a monotone equilibrium as long as mechanisms are invariant (i.e., the set of undominated mechanisms and their ordering with respect to the probability of acceptance does not depend on the anticipated strategy profile α_{-i}).

For instance, in Example 1, there is an equilibrium where sellers with higher reservation value choose higher posted prices as long as higher posted prices are less frequently accepted. Likewise, there is an equilibrium such that sellers with higher reservation value choose auctions with higher reserve prices in Examples 2 and 3.

While the assumption of independently drawn types is not necessary for equilibrium existence in Athey (2001, Theorem 1) where actions are real numbers and can be ordered by the usual relation, the type-independence of the acceptance probability and expected returns in case of acceptance is needed for the Theorem to hold without further restrictions on the set of available mechanisms. If a player's type contains information about the acceptance probability and the expected returns of a mechanism (as for the case of interdependent values), (P, R)–plots do not only depend on the profile α_{-i} that player i anticipates but also on t_i. As a consequence, neither the set of undominated mechanisms

[13] With independently drawn types, Athey (2001, Assumption 1) that ensures a well-defined objective function for every player is trivially satisfied.

nor the ordering of mechanisms has to coincide between (P, R)–plots for different types of player i. In particular, the dominance of a certain mechanism for type t^L does not necessarily imply the dominance for a type $t^H \neq t^L$. However, as long as mechanisms are not only invariant with respect to the anticipated strategy profile but also with respect to types (consider, for instance, different posted prices as in Example 1 or auctions as in Example 2), the existence of a monotone pure strategy equilibrium can be extended to joint densities over types as discussed in Athey (2001, Assumption 1).

4 Auctions Versus Posted Prices

4.1 The Model

As an application of our framework, 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 a reservation value $r_i \in [0, 1]$ for her unit of the indivisible good. For each $i \in \mathcal{S}$, r_i is distributed with a continuous density $h_i(r_i)$ with full support on $[0, 1]$.

$b \geq s + 1$ 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 indivisible good.[14] For each $j \in \mathcal{B}$, v_j is distributed with a 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. If buyer j fails to trade, his utility is zero, if he trades at a price p, his utility is $v_j - p - c$. I.e. buyer j faces a transaction cost of c from trading. We call a buyer a *posted price seeker* if he bears transaction costs distributed with full support on $[0, \widetilde{c})$ for a posted price and transaction costs distributed with full support on $(\widetilde{c}, 1]$ for auctions. All other buyers have constant transaction costs of $0 \leq \widetilde{c} < 1$.

This advantage of auctions as compared to posted prices, however, decreases when buyers do not differ much in their valuations, and posted prices may then be optimal due to reduced uncertainty, immediate transactions, or other perceived virtues of posted prices.[15]

[14] Assuming that the number of buyers (weekly) exceeds the number of sellers is the relevant case for our dataset; see section 5.1

[15] See Wang (1993) for a theoretical treatment of monopolistic sellers and e.g. Mathews (2004) who demonstrate a superiority of posted prices over auctions due to risk aversion or Zeithammer and Liu (2006) who emphasize the impact of time discounting.

Buyers know their own valuation and transaction costs but (as the sellers) only know the distribution of valuations and transaction costs as well as the fraction of posted price seekers in the population. 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 reserve price s_i where $f_i, s_i \in \mathcal{P} \subset [0, 1]$ with $\mathcal{P} = \{0, \delta, 2\delta, \ldots, 1\}$ being a grid with grid step $\delta \leq \frac{1}{2}$.

First, all sellers simultaneously choose a mechanism and then buyers compete for the offered units as follows.

Buyer competition After the sellers' mechanism choice, buyers observe all mechanisms offered by sellers $1, \ldots, s$. Then, buyers decide whether to apply for any of the posted prices offered. Let $\mathcal{B}_i^F$ be the set of buyers who apply for the posted price offered by seller i. The good of seller i who offers posted price f_i is randomly allocated to a buyer in $\mathcal{B}_i^F$ who then pays f_i to seller i. Regarding the choice between posted prices, we assume an incentive consistent behavior as in Peters (1997). I.e., a buyer j has a threshold price $\hat{f}_j$ such that (i) he never applies to a posted prices f with $f > \hat{f}_j$ and (ii) applies to each f with $f \leq \hat{f}_j$ with a type-independent positive probability.[16] Then, all buyers who have not or unsuccessfully applied to a posted price participate in the auctions.

We denote the set of buyers who participate in the auctions by $\mathcal{B}^A$ and their profile of valuations by $\mathbf{v^A}$. Further, we denote the set of sellers who offer auctions by $\mathcal{S}^A$ and their profile of reserve prices by $\mathbf{s^A}$. An important feature of our approach is that we do not need to assume that buyers irreversibly self-select into auctions with different reserve prices. This is important as Peters and Severinov (2006) have shown in a model with a finite grid of valuations that cross-bidding in a competing auction setting (i.e. overbidding the lowest current standing bid by an increment until no-one overbids or the buyer's valuation is reached) forms a Perfect Bayesian Equilibrium for the buyers that yields the same allocation as a sellers' offer double auction for given reserve prices and is – as a result – considered as strategically equivalent to a sellers' offer double auction by the sellers. Indeed, our empirical analysis will show that the reserve price is insignificant for the final auction price after accounting for the fact that selling prices are left-censored

[16] We only require incentive consistency to simplify the exposition. Our central findings will only rely on the existence of mutually beneficial posted prices and are therefore independent of the specific way in which buyer's choose between multiple posted prices.

by reserve prices. This suggests a certain relevance of cross-bidding.

Making use of this insight, we model the interaction between sellers and buyers at the auctions by a simple sellers' offer double auction because. Thus, buyer j submits a threshold value w_j and with a profile of reserve prices s^A and a profile of threshold values w^A, the transaction price p is the $|B^A|$th highest value in (s^A, w^A). All sellers with a reservation value not larger than p trade with all buyers with a threshold strictly larger than p. As at price p the market clears (according to the profiles of reserve prices s^A and thresholds w^A) there is a well-defined pairwise exchange of goods.

With the sellers' choices of mechanisms and the buyers' decisions to apply for a posted price or to participate in the auctions, we have defined a finite action game with incomplete information of sellers and buyers. To determine equilibrium selling and purchasing strategies, we proceed in four steps. Moving backwards, we first analyze equilibrium behavior in the auctions, i.e. the buyers' optimal threshold values and the sellers' optimal reserve prices whenever they choose to offer an auction. Second, we analyze the buyers' decisions between posted prices and auctions. Third, we discuss (P, R)–plots for different design choices by the sellers. Fourth, we discuss equilibrium mechanism choices by the sellers with and without posted price seekers using these (P, R)–plots and our Theorem 1.

4.2 Analysis

Auction The buyers' threshold values $\mathbf{w^A}$ are easily analyzed, as buyers have a weakly dominant strategy to reveal their valuation in a sellers' offer double auction with continuous action space (see e.g. Satterthwaite and Williams, 1989). With a finite grid of admissible prices, this weakly dominant strategy to reveal the valuation translates into a weakly dominant strategy to pick the admissible price which is the largest among all admissible prices that do not exceed the buyer's valuation net of transaction costs.

Lemma 2 *Buyer j has a weakly dominant strategy to set $w_j = \max_{p \in \mathcal{P}: p \leq v_j - c} p$.*

Intuitively, buyers cannot gain from another threshold as a buyer does not trade whenever he influences the price (recall that only buyers whose threshold *strictly* exceed the $|\mathcal{B}^A|$th highest value in $(\mathbf{s^A}, \mathbf{w^A})$ actually trade). Hence, lower thresholds would only reduce the number of instances where the good is purchased at a profitable price and higher thresholds would only add instances where the good is purchased at a non-profitable price.

In contrast, there is a positive probability that a seller determines the price at which she trades so that there is an incentive to overstate the reservation value. Optimal reserve prices are determined by the trade-off between this incentive to overstate the reservation value and the corresponding reduction of the probability to sell the item.

Lemma 3 *When seller i with reservation value r_i offers an auction, her optimal reserve price $s_i^*(r_i)$ (i) satisfies $s_i^*(r_i) \geq r_i$ and (ii) is a non-decreasing function of r_i.*

Choosing reserve prices (and expecting buyers to act according to Lemma 2) establishes a finite action (sub)game with incomplete information between the sellers. We adopt the following notation. When choosing a reserve price, seller i expects m_A other sellers and n_A buyers to be active at the auctions with probability $a_i(m_A, n_A)$. Setting reserve price s_i herself and considering the case of m_A other sellers and n_A buyers at the auctions, the seller expects price p to be the final price at the auctions with probability $l_i(p, s_i, m_A, n_A)$.[17] Accordingly, her expected revenue or utility $U_i^A(r_i, s_i)$ from having reservation value r_i and setting a reserve price s_i reads

$$U_i^A(r_i, s_i) = \sum_{0 \leq m_A \leq s-1, 0 \leq n_A \leq b} a_i(m_A, n_A) \sum_{p \geq s_i} (p - r_i) l_i(p, s_i, m_A, n_A).$$

Proof of Lemma 3. Part (i). If seller i sets reserve price s_i and at least one buyer is active at the auctions (recall that $b \geq s + 1$) there is a strictly positive probability that the final auction price at which seller i trades is indeed s_i. Hence, $s_i < r_i$ is dominated by $s_i = \min_{p \in \mathcal{P}: p \geq r_i} p$.

Part (ii). For the proof of this part, we will utilize Athey (2001, Theorem 1). For independently drawn reservation values and a finite action space as in our model, this theorem indicates that there exists a pure strategy Nash equilibrium in non-decreasing strategies $s_i^*(r_i)$ whenever the *single crossing condition for games of incomplete information (SSC)* (see Athey (2001, Definition 3)) is satisfied for every seller i. SSC is satisfied for seller i if her objective function satisfies *single-crossing of incremental returns (SCP-IR)* (see Athey (2001, Definition 1)) whenever all other sellers $k \neq i$ use a non-decreasing strategy $s_k(r_k)$. Seller i's objective function $U_i^A(r_i, s_i)$ satisfies SCP-IR if for all $s^H > s^L$ and $r^H > r^L$, $U_i^A(r^L, s^H) \geq (>) U_i^A(r^L, s^L)$ implies $U_i^A(r^H, s^H) \geq (>) U_i^A(r^H, s^L)$. To see that seller i's objective function $U_i^A(r_i, s_i)$ satisfies SCP-IR, consider $r^H > r^L = r^H - \ell \cdot \delta$ and $s^H > s^L$. Then,

$$U_i^A(r^H, s^H) = \sum_{m_A, n_A} a_i(m_A, n_A) \sum_{p \geq s^H} (p - r^H) l_i(p, s^H, m_A, n_A)$$

[17] Both probability distributions $a(.,.)$ and $l(., s_i, m_A, n_A)$ certainly depend on the strategy profile of sellers and buyers that seller i anticipates. We do not mention this dependence for expositional ease.

$$= \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^H} (p - r^L - \ell \cdot \delta) l_i(p, s^H, m_A, n_A)$$
$$\geq \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^L} (p - r^L) l_i(p, s^L, m_A, n_A) - \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^H} \ell \cdot \delta \cdot l_i(p, s^H, m_A, n_A)$$
$$\geq \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^L} (p - r^L) l_i(p, s^L, m_A, n_A) - \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^L} \ell \cdot \delta \cdot l_i(p, s^L, m_A, n_A)$$
$$= \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p \geq s^L} (p - r^L - \ell \cdot \delta) l_i(p, s^L, m_A, n_A) = U_i^A(r^L, s^L).$$

The first inequality follows from $U_i^A(r^L, s^H) \geq U_i^A(r^L, s^L)$. The second inequality is implied by $\sum_{p \geq s^H} l_i(p, s^H, m_A, n_A) \leq \sum_{p \geq s^L} l_i(p, s^L, m_A, n_A)$ for all m_A and n_A. Similarly, $U_i^A(r^L, s^H) > U_i^A(r^L, s^L)$ implies a strict inequality. Hence, $U_i^A(r_i, s_i)$ satisfies SCP-IR for every seller i and a given profile of the other sellers' strategies such that the (sub)game of reserve price choice satisfies SCC and Athey (2001, Theorem 1) implies Part (ii). ■

Posted prices The following Lemma characterizes sellers' optimal choices of posted prices given that they choose a posted-price mechanism at all:

Lemma 4 *When seller i with reservation value r_i offers a posted price, her optimal posted price $f_i^*(r_i)$ (i) satisfies $f_i^*(r_i) \geq r_i$ and (ii) is a non-decreasing function of r_i.*

Proof. Part (i). If seller i sets posted price f_i, his profit is $(f_i - r_i)$ whenever the posted price is executed. Hence, $f_i < r_i$ is dominated by $f_i = \min_{p \in \mathcal{P}: p \geq r_i} p$.

Part (ii). As in the proof of Lemma 3, we will utilize (Athey 2001, Theorem 1) to show the existence of a pure strategy Nash equilibrium in non-decreasing strategies. For the optimal choice of a posted price, seller i's objective function is $U_i^F(r_i, f_i) = Q(f_i)(f_i - r_i)$ where $Q(f_i)$ denotes the probability that a posted price f_i is executed. Note that $Q(f^H) \leq Q(f^L)$ for any $f^H > f^L$. To see that seller i's objective function $U_i^F(r_i, f_i)$ satisfies SCP-IR, consider $f^H > f^L$ and $r^H > r^L = r^H - \ell \cdot \delta$, and suppose that $U_i^F(r^L, f^H) \geq (>) U_i^F(r^L, f^L)$. Then,

$$U_i^F(r^H, f^H) = Q(f^H)(f^H - r^H) = Q(f^H)(f^H - r^L - \ell \cdot \delta)$$
$$\geq Q(f^L)(f^L - r^L) - Q(f^H) \cdot \ell \cdot \delta \geq Q(f^L)(f^L - r^L) - Q(f^L) \cdot \ell \cdot \delta = U_i^F(r^H, f^L).$$

The first inequality follows from $U_i^F(r^L, f^H) \geq U_i^F(r^L, f^L)$ and the second inequality from $Q(f^H) \leq Q(f^L)$. Similarly, $U_i^F(r^L, f^H) > U_i^F(r^L, f^L)$ implies a strict inequality. Hence, $U_i^F(r_i, f_i)$ satisfies SCP-IR for every seller i and a given profile of the other sellers' strategies so that the (sub)game of posted price choice satisfies SCC and (Athey 2001, Theorem 1) implies Part (ii). ■

Buyers' Choices Between Auction and Posted Prices When deciding upon the threshold posted price f_j buyer j is willing to execute, buyer j compares his utility from a posted price transaction at a posted price f, $U_j^F = v_j - f - c$ with the expected utility $U_j^A(v_j)$ from being active at the auctions (anticipating behavior as described in Lemma 2)

$$U_j^A(v_j) = \sum_{0 \le n_A \le b-1, 0 \le m_A \le s} a_j(m_A, n_A) \sum_{p < v_j - c} (v_j - p - c) l_j(p, v_j, m_A, n_A)$$

where $a_j(m_A, n_A)$ is the probability with which buyer j expects n_A other buyers and m_A sellers to be active at the auctions and $l_j(., v_j, m_A, n_A)$ is the probability distribution over market clearing prices from buyer j's perspective. Hence, buyer j considers a posted price f *profitable* if $(v_j - c - f) \ge U_j^A(v_j)$.

Likewise, seller i considers a posted price offer f profitable if the expected revenue from the posted price transaction $U_i^F = Q(f)(f - r_i)$ (weakly) exceeds her expected optimal auction revenue $U_i^A(r_i, s_i^*(r_i))$. A profitable posted price f of seller i therefore satisfies $f \ge \frac{1}{Q(f)} U_i^A(r_i, s_i^*(r_i)) + r_i$.

To summarize, a posted price f is profitable for buyer j and seller i if $v_j - c - U_j^A(v_j) \ge f \ge \frac{1}{Q(f)} U_i^A(r_i, s_i^*(r_i)) + r_i$. In particular, for a posted price transaction at a price f, mutual profitability for the pair of buyer j and seller i requires that

$$v_j - c - r_i \ge U_j^A(v_j) + \frac{1}{Q(f)} U_i^A(r_i, s_i^*(r_i)). \tag{1}$$

Dominated Mechanisms A necessary condition for a posted price offer to be better than an auction for seller i is that a positive mass of buyers considers the posted price profitable such that Ineq. 1 is satisfied for r_i and a set of buyers, i.e. a positive measure of valuations v_j.

A potential problem for a clear-cut evaluation of Ineq. 1 is that each trader may expect a different market clearing price at the auctions because a seller's reserve price may actually be the market clearing price and buyers and sellers may hold differing beliefs regarding the number of traders at the auction. For the results in the remainder of this section, however, we only need to consider the configuration where a seller expects all other sellers to conduct an auction and where buyers face only one posted price. In this case, the difference between the expected market clearing price as computed by seller i

$$\overline{p}_i^S = \sum_{m_A, n_A} a_i(m_A, n_A) \sum_{p \ge 0} p \cdot l_i(p, s_i, m_A, n_A)$$

and the expected market clearing price as computed by buyer j

$$\overline{p}_j^B = \sum_{m_A,n_A} a_j(m_A,n_A) \sum_{p\geq 0} p \cdot l_j(p,v_j,m_A,n_A)$$

shrinks as the number of buyers and sellers grows large. For a large market, the probability that seller i's reserve price determines the market clearing price tends to zero and so does the difference between market clearing prices for one more seller or buyer. We regard the maximal difference between market clearing prices as expected by a seller i and a buyer j as a measure for the homogeneity of expectations regarding the final auction price.

Definition 4 *A market* $(\mathcal{B},\mathcal{S})$ *has* heterogeneity of expectations $\Delta\overline{p}$ *if*

$$\Delta\overline{p} = \max\{|\overline{p}_i^S - \overline{p}_j^B|| \forall i \in \mathcal{S}, j \in \mathcal{B}\}.$$

If heterogeneity of expectations is sufficiently small, it is straightforward to see that no posted price is mutually profitable in the absence of posted price seekers. This is different to Hammond (2013) where posted prices are profitable even without transaction costs as there is no cross-bidding, and because sellers prefer to be in a mechanism market with fewer rivals.

Proposition 1 *Suppose there are no posted price seekers. If heterogeneity of expectations is sufficiently small, there is no mutually profitable posted price.*

Proof. If expectations had heterogeneity $\Delta\overline{p} = 0$, we could rewrite the surplus of trade between buyer j and seller i as follows

$$v_j - c - r_i = (v_j - c) \cdot \sum_{m_A,n_A} a_j(m_A,n_A) \sum_p l_j(p,v_j,m_A,n_A) - r_i \sum_{m_A,n_A} a_i(m_A,n_A) \sum_p l_i(p,s_i,m_A,n_A)$$

$$= (v_j - c) \cdot \sum_{m_A,n_A} a_j(m_A,n_A) \sum_p l_j(p,v_j,m_A,n_A) - \overline{p}_j^B + \overline{p}_i^S - r_i \cdot \sum_{m_A,n_A} a_i(m_A,n_A) \sum_p l_i(p,s_i,m_A,n_A)$$

$$= \sum_{m_A,n_A} a_j(m_A,n_A) \sum_p (v_j - c - p) \cdot l_j(p,v_j,m_A,n_A) + \sum_{m_A,n_A} a_i(m_A,n_A) \sum_p (p - r_i) \cdot l_i(p,s_i,m_A,n_A)$$

$$= U_j^A(v_j) + U_i^A(r_i,s_i)$$

$$+ \sum_{m_A,n_A} a_j(m_A,n_A) \sum_{p\geq v_j - c} (v_j - c - p) \cdot l_j(p,v_j,m_A,n_A) + \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p<s_i} (p - r_i) \cdot l_i(p,s_i,m_A,n_A)$$

$$< U_j^A(v_j) + \frac{1}{Q(f_i)} U_i^A(r_i, s_i^*(r_i))$$

For the first equality, we just used the fact that $a_{i,j}$ and $l_{i,j}$ are probability distributions. The last inequality follows from the fact that

$$\sum_{m_A,n_A} a_j(m_A,n_A) \sum_{p\geq v_j-c} (v_j-c-p)\cdot l_j(p,m_A,n_A) + \sum_{m_A,n_A} a_i(m_A,n_A) \sum_{p<s_i} (p-r_i)\cdot l_i(p,m_A,n_A) \leq 0$$

with a strict inequality if either $r_i > 0$ (and therefore $s_i > 0$) or $v_j < 1$ as $p = 0$ and $p = 1$ are in $\mathcal{P}$ and occur with positive probability. But if $r_i = 0$, $f_i = 0$ is not profitable as $U_i^A(0,0) > 0$ (recall that $s \leq b+1$). Therefore $Q(f_i) < 1$ has to hold for any profitable posted price because with a strictly positive probability all buyers have a valuation below $f_i > 0$. Hence, Ineq. 1 is violated for every pair of seller and buyer if the heterogeneity of expectations is sufficiently small as indicated by the Proposition. ■

$(\mathbf{P},\mathbf{R})$–plots With Proposition 1, we can now discuss the structure of (P,R)–plots for sufficiently small heterogeneity of expectations and in the absence of posted price seekers. Consider seller i and suppose that she expects all other sellers to offer auctions following a monotone strategy α_{-i} as depicted in Lemma 3. The auctions (i.e. reserve prices $s_i \in \mathcal{P}$) that seller i can offer are represented in the (P,R)–plot as the set of points

$$\left\{ \left(\sum_{p\geq s_i} l_i(p,s_i,s,b), R_i(s_i,\alpha_{-i}) \right) \middle| \, s_i \in \mathcal{P} \right\}$$

where $R_i(s_i,\alpha_{-i})$ denotes the expected revenue in case of selling. Note, in particular, that this set contains the point $(0,1)$, as the selling probability is zero for a reserve price of 1, and the point $(1,\overline{p}_i^S)$ as the selling probability is one for $s_i = 0$.

When seller i offers a posted price f_i the selling probability is zero for all $f_i \geq \overline{p}_i^S$ as otherwise a seller with $r_i = 0$ (who expects $\overline{p}_i^S$ from conducting an auction) could establish mutually beneficial posted price trading with a positive mass of buyers in contradiction to Proposition 1. For $f_i < \overline{p}_i^S$ there may be a positive mass of buyers who consider trade at f_i profitable, but this mass is bounded away from 1 as long as $f_i > 0$. Trivially, the (P,R)–plot for posted prices contains the point $(1,0)$ as a posted price of zero is sold with probability 1. Hence, posted prices are represented in the (P,R)–plot by points with $P = 0$ for $f \geq \overline{p}_i^S$, $0 \leq P < 1$ for $0 \neq f \leq \overline{p}_S^i$, and $P = 1$ for $f = 0$. This illustrates the result in Proposition 1 that, absent transaction costs, posted prices are dominated mechanisms in the (P,R)–plot of any seller i regardless of the profile of mechanisms that she anticipates, and will not be offered in equilibrium. Hence, in the absence of posted price seekers, the set of available mechanisms is invariant and auctions (i.e., the

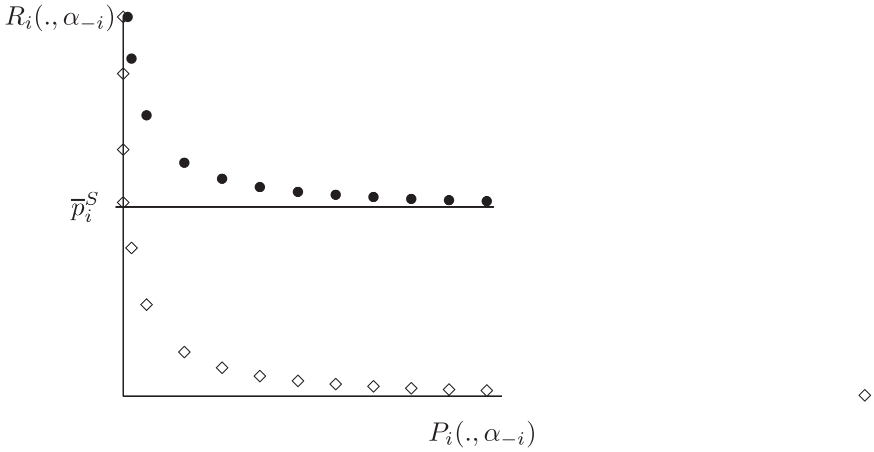

Figure 3: Posted prices (diamonds) and auctions (bullets) without posted price seekers.

set of undominated mechanisms) can be ordered according to their reserve price such that Theorem 1 guarantees the existence of a monotone pure strategy equilibrium where sellers with higher reservation value choose auctions with higher reserve prices.

We now turn to our setting that yields the hypotheses which will be empirically tested with our data from ticket sales. Suppose that $\widetilde{c} \geq \delta$ and that there is a probability $\epsilon > 0$ for a buyer to be a posted price seeker. Then, any posted price $f \leq 1-\delta$ will be accepted with a positive probability: A posted price seeker has transaction costs at the auction that absorb all his valuation and almost vanishing transaction costs for a posted price with a positive probability. So if he has a valuation exceeding $1-\delta$, incentive consistency implies that he applies for a posted price of $1-\delta$ with a positive probability. If $\widetilde{c} \geq \delta$, a seller with $1-\delta \geq r \geq 1-2\delta$, i.e. a seller who has to receive at least $1-\delta$ will never trade at an auction but sell with a positive probability at $f = 1-\delta$. Therefore $f = 1-\delta$ is not dominated as the revenue of $1-\delta$ will never be expected in an auction but $f = 1-\delta$ is sold with a positive probability. Now observe that posted prices $f \geq \overline{p}_S^i$ will only be accepted by posted price seekers, i.e. at most with probability ϵ. Hence, if $\epsilon > 0$ is sufficiently small, the set of mechanisms is invariant with undominated mechanisms being a posted price $f = 1-\delta$ (with a positive selling probability bounded by ϵ) and auctions with reserve prices up to $1-2\delta$ and selling probabilities larger than ϵ. In other words we get single crossing for (P, R)–plots of posted prices and auctions in such a way that posted prices yield a higher revenue in case of trade for sufficiently small but positive trading probabilities and auctions yield higher revenues in case of trade for large trading probabilities (see Figure 4). As the set of mechanisms is invariant, Theorem 1 indicates that there exists a pure strategy equilibrium in monotone strategies such that high valuation sellers offer posted prices, while low valuation sellers offer auctions. We summarize as follows:

Proposition 2 *Suppose $\tilde{c} \geq \delta$ and let the heterogeneity of expectations be sufficiently small. Then, there is $\tilde{\epsilon} > 0$ such that for all ϵ with $0 < \epsilon \leq \tilde{\epsilon}$ there is a $\tilde{r}(\epsilon) \in (0,1)$ with seller i offering an auction if $r_i \leq \tilde{r}(\epsilon)$ and offering a posted price if $r_i > \tilde{r}(\epsilon)$.*

4.3 Testable Hypotheses

Our theoretical findings imply the following testable hypotheses.

As buyers choose between posted prices in an incentive consistent way, the probability that the good is sold at a posted price f, $Q(f)$, is non-increasing in f. Likewise, as buyers choose the maximal feasible price weakly below their valuation as a threshold value in the auction, the probability that the good is sold at an auction with reserve price s_i is non-increasing in s_i:

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

When analyzing final auction prices, we need to take into account that observed prices are left censored to reserve prices. Thus, without correcting for censoring, auction prices are increasing in reserve prices (see Hypothesis 2a). Due to cross-bidding, however, final auction prices should be independent of the reservation price when the corresponding regression corrects for censoring (see Hypothesis 2b).

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

Since the envelope of a (P,R)–plot (i.e. the set of undominated mechanisms) is decreasing, Hypothesis 1 also implies that the lower a start price of an undominated mechanism, the more to the south-east the corresponding mechanism is in the (P,R)–plot.

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 expressed in Proposition 2 also implies several Hypotheses regarding the relative position of posted prices and auctions in the (P,R)–plot (for an illustration see Figure 4). If auctions dominate posted prices if and only if the selling probability exceeds a threshold $\hat{P}$ and sellers do not choose dominated mechanisms, the selling probabilities of auctions and posted prices should differ significantly.

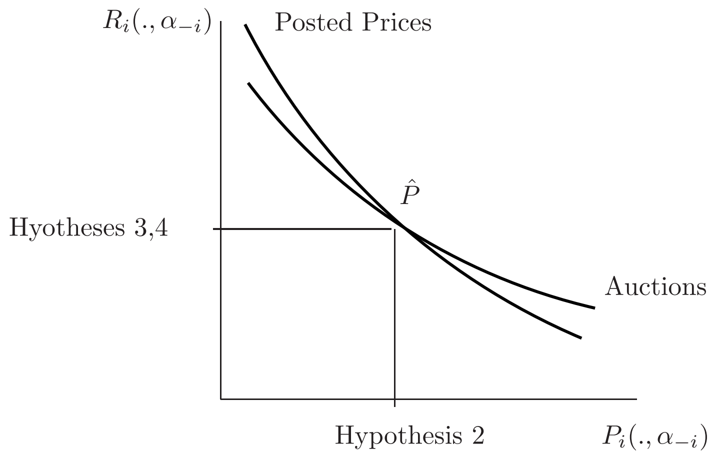

Figure 4: Single-crossing (P, R)–plot and Hypotheses 2–4.

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.*

If it is indeed optimal that high valuation sellers offer posted prices, we should expect posted prices to be sold more frequently as compared to equally high reservation prices.

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

Finally, equilibrium mechanism choice as described in Proposition 2 implies an interaction effect between the auction dummy and the selling probability when describing the revenue difference between auctions and posted prices. Due to the single-crossing property of (P, R)–plots, all auctions with selling probabilities below (above) that intersection of (P, R)–plots are dominated by (dominate) 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 empirically testable hypothesis is thus that, when selling probabilities are the same for both selling modes, auctions lead to higher expected revenues for low probabilities, while posted prices are superior for high probabilities:

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

5 Empirical Analysis

We proceed as follows: First, we describe the data and discuss why we have chosen ticket sales. We then first confirm our hypotheses that refer to one of the two mechanisms, and then turn to the comparison of auctions and posted prices. In particular, we test our main hypothesis that, for identical selling probabilities, auctions yield higher revenues if and only if these probabilities are high. We do so by calculating, for each reserve price observed in an auction, the posted price that would have matched the auction's selling probability had the item been offered under that selling mode. This makes the two selling modes comparable, even though they differ with respect to start prices and the impact of those start prices on selling probabilities. We then regress the difference between the actual auction price and the estimated posted price on selling probabilities which are identical for both sales modes.

5.1 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 game of the championship. Altogether, 31 games were played, including 24 games 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.

We have chosen ticket sales for 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 considerably 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 in 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. Since we are interested in the heterogeneity of sellers' preferences, a perishable good is, therefore, most suitable for our analysis.

Third, an important assumption of our approach is that the number of buyers (weekly) exceeds the number of sellers. Although we cannot identify the number of buyers for each event in our data set, it seems straightforward that the number of buyers considerably 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,[18] so that our data certainly fulfills the requirement that $b \geq s$.

Tickets were originally sold by the United European Football Association (UEFA) and the regarding national football associations. Because of excess demand, tickets were distributed in a lottery among the applicants in the end of January 2008.[19] In each game, 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 games in the preliminary round, up to €550 for the highest quality 1 in the final. A seller's type t_i in the model can be interpreted as the utility from watching the game 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 at February 1, 2008 and distinguish postings with respect to

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

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

the game 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.[20] 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 use reserve prices, and we will refer to both the reserve price in an auction and the posted price as the *start price*. For making prices for different games 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. We will refer to these variables in the subsequent subsection in some more detail. The distribution of ticket categories represents their relative magnitude 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.[21] 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 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 transaction 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.

[20]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.

[21]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 soccer fans prefer buying at least two tickets in order to share the experience.

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.[22] Finally, the literature has shown that prices may depend on the duration of postings and on the weekday and time when an auction ends.[23] 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%).

5.2 A First Look at Start Prices, Selling Probabilities and Selling Prices

Recall from section 4.3 that Hypotheses 1 and 2 refer to a separate analysis of auctions and posted prices, while all other hypotheses compare the two mechanisms. The first two columns of table 2 show that the selling probabilities are significantly decreasing in the posted prices and the reserve prices, respectively (see Hypothesis 1). The next two columns consider the impact of reserve prices on the actual selling prices for auctions. In column 3, we run a simple OLS-model. Then, the reserve price is highly significantly positive as predicted by Hypothesis 2a. The problem with OLS estimations, however, is that unsold items, for which we would observe low prices if it was not for the high start price, are neglected. As OLS parameter estimates are thus upwards biased, we then 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 reserve price. In line with Hypothesis 2b and our assumption of cross-bidding, we then find no impact of reserve prices on final auction prices.

We now proceed to the comparison of posted prices and auctions. In line with *Hypothesis 4* from our theoretical model, table 1 on descriptive statistics shows that the mean posted price amounts to more than the quintuple of the original price (5.73), while the mean reserve price for auctions is far below one (around 0.34). The main reason for this

[22]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.

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

huge difference is that around 86% of auction sellers do not set a reserve price, and the minimum reserve price of €1 is assigned to these auctions. When restricting attention to reserve prices weakly above the original ticket price, then the average mark-up in auctions is about four which means that, if applied at all, reserve prices are high. 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 OLS regressions with regard to start prices (model 1) and selling prices (model 3), and a binary probit for estimating the selling probability (model 2). 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 reserve prices in auctions are, on average, below posted prices. As for the control variables, we find that start prices are higher for tickets of inferior categories and for bundles of tickets, which can be attributed to the fact that the willingness to pay for watching matches by-oneself is lower. Furthermore, the start price is slightly lower when the number of simultaneous auctions for the same match is high.

The results of the binary probit estimations on the selling probability in column 2 displays 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.

To compare the selling prices for the two trading mechanisms, we again need to take into account that OLS estimations would neglect unsold items, and would hence be upwards biased. In line with Hypothesis 5, the censored normal regression model 3 in table 3 shows that the selling price is considerably lower for auctions. Turning to the control variables, 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 for the same match and the same category of tickets. As expected, 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.[24] However, start prices, selling probabilities and selling prices are not independent from each other. We will empirically explore these interdependencies in the following section.

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

The regression analyses in table 3 confirms the impression from the descriptive statistics that there are large differences between auctions and posted prices with respect to start prices, the fraction of successfully sold items, and selling prices. To provide more detailed information, table 4 disaggregates by intervals of start prices. This is useful as start prices are considerably higher for posted prices, so that the disaggregation sheds light on the impact of the 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 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

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

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, for the three intermediate intervals it is insignificant, and it is significantly negative only for the interval with mark-ups above six. Hence, when we disaggregate by intervals, we no longer find that the mark-ups for sold items are always higher for posted prices.

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. Consequently, in order to gain a better understanding on the actual impact of the selling mode on selling probabilities and revenues, we 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.[25] 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 reserve price.

The 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: The probit model for this regression is given by

$$p_i = \begin{cases} \Phi\left(\hat{\beta}_0 + \hat{\beta}_S \ln S_i + \hat{\beta}_A + \hat{\beta}_{\mathbf{x}} \mathbf{x_i}\right), & \text{if } i \text{ is auctioned;} \\ \Phi\left(\hat{\beta}_0 + \hat{\beta}_S \ln S_i + \hat{\beta}_{\mathbf{x}} \mathbf{x_i}\right), & \text{if } i \text{ is offered at a posted price,} \end{cases} \tag{2}$$

where $\Phi(.)$ 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

[25] 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 tow sales modes, models (3) and (4) consider auctions and posted prices in separate regressions. 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:

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

$$p_i^F = \Phi\left(\hat{\beta}_0^F + \hat{\beta}_S^F \ln S_i + \hat{\beta}_{\mathbf{x}}^{\mathbf{F}} \mathbf{x_i}\right) = \Phi(\hat{y}_i^F) \tag{4}$$

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.

5.4 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 aforementioned empirical finding that the impact of start prices on selling probabilities is more pronounced for auctions indeed suggests that auctions may only be superior for high selling probabilities.

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 reserve 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 (2) 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 (2), and equate both cases. Solving for F_i yields

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

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

$$ESP_i = R_i - F_i = R_i - e^{\hat{\beta}_A/\hat{\beta}_S} S_i. \tag{6}$$

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. Note carefully that, since (P, R)-plots are a concept related 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.[26] 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 the 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.[27]

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 the posted prices. For

[26]Note that, since (P, R)-plots are a concept related to revenue *conditional on sale*, the regressions in table 7 include only sold items and, thus, do not require a censored normal regression. Doing this, the number of observations is reduced to n=10,409.

[27]Note that with equilibrium behavior as analyzed in our model (i.e., with homogenous (equilibrium) beliefs, homogenous discounting, and no noise) we should observe either *only* posted prices or auctions for a given selling probability. Empirically, however, we observe a coexistence of the two mechanisms even for identical selling probabilities, and we make use of these observations in our estimation technique.

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 (3) 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 (3) and (4):

$$F_i' = e^{(\hat{y}_i^A - \hat{\beta}_0^F - \beta_{\mathbf{x}}^{\hat{\mathbf{F}}} \mathbf{x_i})/\hat{\beta}_S^F} = e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F} \tag{7}$$

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

$$ESP_i' = R_i - F_i' = R_i - e^{(\hat{y}_i^A - \hat{y}_i^F + \hat{\beta}_S^F \ln S_i)/\hat{\beta}_S^F}. \tag{8}$$

Model (2) of table 7 shows that our main result that the excess return of auctions is decreasing in the start price (and thus increasing in the desired selling probability) is robust.[28] 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 reserve price in table 7 confirmed our 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 (3) and (4), respectively. Then, the (P, R)-plot for posted prices is

[28]Another objection could be that, due to the high number of auctions without any reserve price set, 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 reserve 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 (4), as revenue conditional on sale is equal to the start price. As this will typically not be the case for auctions, we need to estimate the relationship between reserve prices and revenue conditional on sale first. The empirical model for this estimation is:[29]

$$R_i = \hat{\alpha}_0 + \hat{\alpha}_S S_i + \hat{\alpha}_{\mathbf{x}} \mathbf{x_i}. \tag{9}$$

Solving (9) for S_i and substituting for S_i in (3) 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.

6 Concluding Remarks

The model of competing mechanisms in Section 3 offers a general discussion of the trade-off between prices conditional on sale and the selling probability, and its implications for the existence of monotone equilibria in a framework of private values. As the existence theorem for monotone equilibria in Athey (2001) is formulated for types drawn from an atomless *joint* probability distribution (thereby allowing for interdependent values), it is worthwhile to discuss how essential the assumption of private values actually is. In the proof of our Theorem 1, we only need the assumption of private values to guarantee that the set of undominated mechanisms (and its ordering) for a given strategy of other sellers does not depend on a seller's type. Consider, for instance, the comparison of posted prices and auctions in a set-up with correlated valuations of sellers and buyers. A low valuation seller (who expects buyers to have predominately low valuations) may then consider an auction with a high reserve price inferior to a high posted price as the auction is unlikely to be visited by a buyer, whereas the posted price may be attractive to buyers with large auction specific transaction costs. In contrast, a high valuation seller (who expects buyers to have high valuations) may consider the same auction superior to the posted price as she expects multiple high valuation buyers to participate in the auction. However, as long as all available mechanisms can be easily ordered according to their acceptance probability (consider, for instance, auctions with different reserve prices), our Theorem 1 can be extended to joint probability distributions as in Athey (2001), Theorem 1.

[29] The result of this estimation is given in table 10 in the Appendix.

The specific model in Section 4 utilizes the existence of monotone equilibria to confirm the well-known superiority of auctions in the absence of auction specific transaction costs and demonstrates the single-crossing of optimal mechanisms in the presence of transaction costs. In our model, these results are based on the ability of competing auctions (with cross-bidding) to retrieve market clearing prices – and the inability of posted prices to offer mutually beneficial deals as long as buyers and sellers have sufficiently similar expectations regarding 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)). But even in a model that favors auctions in this way, we can demonstrate that auctions are no longer superior whenever transaction costs are taken into account (as also emphasized in the literature on monopolistic auction design). 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 modelling competition between auctions and posted prices. E.g., the same outcome would result in a model where posted prices remain valid and buyers execute a posted price only if the market price reaches the posted price, or in a model where buyers and sellers do not differ too much in their beliefs regarding final auction prices and sellers can costlessly replace posted prices by auctions. If all buyers engaged in sniping (i.e. wait until the last minute of an auction and submit an incremental bid above the reservation price), then an auction with reserve price f and a posted price $f + \delta$ would result in identical selling probabilities and prices in the absence of institution specific transaction costs. But as soon as a fraction of buyers cross-bid as in our model, our results can be restored. In contrast, however, posted prices would certainly become more attractive for sellers if buyers systematically overshot with their expectations of market clearing prices (e.g. due to a representativeness bias). As long as only a small group of buyers is expected to exhibit this bias, we would still recover the single-crossing result as obtained in our model and tested with our data.

Empirically, we have used ticket sales for the European Soccer 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. To the best of our knowledge, our paper is the first to compare the revenues from posted prices and auctions with identical selling probabilities. Controlling for selling probabilities is, in our view, an appropriate way of making the revenues from auctions and posted prices comparable to each other (without a reference to seller experiments as in Einav et al. (2013)). Hence, the empirical strategy follows the theoretical model which identifies the undominated (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 envelope of 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. Hence, we might say that 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. For any selling probability that a seller may prefer, our analysis, therefore, identifies her optimal mechanism choice. Note that, for such a conclusion, unobserved heterogeneity on reservation values is no problem: The reservation value determines the optimal selling probability, but for a given selling probability, the mechanism that yields higher revenue is superior for each seller type.

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***		
	(0.0453)	(0.0387)		
Start Price			0.0767**	-0.0163
			(0.0371)	(0.0330)
Days left to match	0.0400**	-0.0367***	-0.1138***	-0.1084***
	(0.0197)	(0.0106)	(0.0218)	(0.0215)
Days left to match squared	-0.0036**	0.0022***	0.0040**	0.0035*
	(0.0016)	(0.0007)	(0.0019)	(0.0019)
Number of competing offers	-0.0004	-0.0010***	-0.0053***	-0.0052***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
End of auction (dummies)				
Saturday (d)	0.0152	-0.0222	0.0978**	0.1017***
	(0.0366)	(0.0154)	(0.0389)	(0.0389)
Sunday (d)	-0.0194	-0.0480***	-0.0627**	-0.0631**
	(0.0328)	(0.0182)	(0.0283)	(0.0282)
Evening (6 to 10pm) (d)	-0.0577**	-0.0069	-0.0459*	-0.0585**
	(0.0231)	(0.0079)	(0.0265)	(0.0263)
Ticket quality (base: top quality)				
Medium quality	0.0454	0.0575***	0.6071***	0.5987***
	(0.0409)	(0.0154)	(0.0301)	(0.0301)
Regular seats	0.2870***	0.1108***	2.7241***	2.7292***
	(0.0290)	(0.0186)	(0.0385)	(0.0384)
Number of offered tickets (base: 1)				
2 tickets	0.0633	0.0551***	0.6549***	0.6528***
	(0.0421)	(0.0151)	(0.0365)	(0.0363)
3 or more tickets	0.0415	0.0322***	0.4918***	0.4842***
	(0.0424)	(0.0109)	(0.0525)	(0.0523)
Duration of posting (base: 3 days)				
5 days	0.0837***	0.0210**	0.2845***	0.2961***
	(0.0251)	(0.0093)	(0.0323)	(0.0321)
7 days	0.1009***	0.0306***	0.3552***	0.3658***
	(0.0290)	(0.0107)	(0.0336)	(0.0336)
10 days	0.0562	0.0508***	0.4615***	0.4635***
	(0.0420)	(0.0129)	(0.0408)	(0.0407)
Intercept			2.5962***	2.6108***
			(0.1694)	(0.1659)
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 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***
	(0.0843)	(0.0144)	(0.0515)
Days left to match	0.0094	-0.0071***	-0.1151***
	(0.0226)	(0.0027)	(0.0206)
Days left to match squared	-0.0021	0.0004*	0.0038**
	(0.0019)	(0.0002)	(0.0018)
Number of competing offers	-0.0008**	-0.0002***	-0.0056***
	(0.0003)	(0.0000)	(0.0003)
End of auction (dummies)			
Saturday	0.0582	-0.0095	0.1075**
	(0.0475)	(0.0062)	(0.0423)
Sunday	-0.0114	-0.0102**	-0.0758***
	(0.0344)	(0.0046)	(0.0273)
Evening (6 to 10pm)	-0.1534***	0.0022	-0.0647**
	(0.0331)	(0.0037)	(0.0259)
Ticket quality (base: top quality)			
Medium quality	0.1870***	-0.0078	0.5853***
	(0.0337)	(0.0050)	(0.0318)
Regular seats	0.6629***	-0.0041	2.7447***
	(0.0452)	(0.0052)	(0.0394)
Number of offered tickets (base: 1)			
2 tickets	0.1280***	0.0058	0.6794***
	(0.0402)	(0.0053)	(0.0374)
3 or more tickets	0.2368***	-0.0086	0.5197***
	(0.0652)	(0.0071)	(0.0520)
Duration of posting (base: 3 days)			
5 days	-0.0236	0.0166***	0.2935***
	(0.0406)	(0.0038)	(0.0312)
7 days	-0.0161	0.0206***	0.3799***
	(0.0380)	(0.0040)	(0.0343)
10 days	0.0791	0.0159***	0.4928***
	(0.0555)	(0.0041)	(0.0398)
Intercept	5.1128***		2.9360***
	(0.2560)		(0.1536)
Match Dummies	Yes	Yes	Yes
Observations	12,315	12,315	12,315

Robust standard errors 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 Reserve 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***
	(0.1624)	(0.1276)	(0.1139)	(0.0977)	(0.0858)	(0.5547)	(0.0515)
Days left to match	-0.1045***	0.0182	-0.0522	-0.1338**	-0.1256***	-0.8242***	-0.1151***
	(0.0221)	(0.0928)	(0.0622)	(0.0633)	(0.0443)	(0.1738)	(0.0206)
Days left to match squared	0.0034*	-0.0031	-0.0007	0.0078	0.0063**	0.0545***	0.0038**
	(0.0019)	(0.0084)	(0.0043)	(0.0048)	(0.0029)	(0.0144)	(0.0018)
Number of competing offers	-0.0051***	-0.0025*	-0.0034***	-0.0037***	-0.0030***	-0.0205***	-0.0056***
	(0.0003)	(0.0015)	(0.0013)	(0.0012)	(0.0011)	(0.0039)	(0.0003)
End of auction (dummies)							
Saturday	0.0826**	0.0728	0.1753	0.2309	0.0104	0.1973	0.1075**
	(0.0393)	(0.1592)	(0.1902)	(0.1631)	(0.1057)	(0.5303)	(0.0423)
Sunday	-0.0628**	-0.0436	-0.0712	-0.0094	-0.1151	-0.6678	-0.0758***
	(0.0284)	(0.1453)	(0.1067)	(0.1170)	(0.1005)	(0.4501)	(0.0273)
Evening (6 to 10pm)	-0.0606**	0.1209	-0.0773	0.0732	0.0624	-0.5784*	-0.0647**
	(0.0264)	(0.0974)	(0.0826)	(0.0793)	(0.0681)	(0.2989)	(0.0259)
Ticket quality (base: top quality)							
Medium quality	0.6052***	0.1134	0.2681***	0.1933*	0.2358**	0.1234	0.5853***
	(0.0302)	(0.1161)	(0.0993)	(0.0998)	(0.1056)	(0.7275)	(0.0318)
Regular seats	2.7382***	1.4344***	1.4105***	0.8409***	0.9959***	2.7233***	2.7447***
	(0.0391)	(0.2255)	(0.2122)	(0.1893)	(0.1565)	(0.5977)	(0.0394)
Number of offered tickets (base: 1)							
2 tickets	0.6547***	-0.0914	0.5014**	0.3880***	0.4773***	1.3441**	0.6794***
	(0.0364)	(0.1637)	(0.2300)	(0.1277)	(0.1136)	(0.6024)	(0.0374)
3 or more tickets	0.4792***	0.0174	0.4790**	0.3343***	0.4107***	0.6720	0.5197***
	(0.0522)	(0.2142)	(0.2264)	(0.1258)	(0.1104)	(0.5817)	(0.0520)
Duration of posting (base: 3 days)							
5 days	0.2820***	0.4139**	0.3988**	0.1178	0.3174**	-0.5968*	0.2935***
	(0.0320)	(0.2038)	(0.1557)	(0.0968)	(0.1570)	(0.3464)	(0.0312)
7 days	0.3519***	0.3571**	0.0963	0.2560**	0.2709***	0.1956	0.3799***
	(0.0339)	(0.1577)	(0.1324)	(0.1093)	(0.0938)	(0.4213)	(0.0343)
10 days	0.4415***	0.5989**	0.5327***	0.1584	0.3830***	0.4485	0.4928***
	(0.0414)	(0.2398)	(0.1323)	(0.1060)	(0.0946)	(0.3304)	(0.0398)
Intercept	1.5135***	2.4889***	2.6176***	3.4805***	4.9319***	4.0718***	2.9360***
	(0.2265)	(0.1848)	(0.3597)	(0.2126)	(0.1754)	(1.0255)	(0.1536)
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 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) (d)	0.4091***	-0.1169***		
	(0.0144)	(0.0144)		
ln Start Price		-0.5735***	-0.6258***	-0.2455***
		(0.0298)	(0.0453)	(0.0387)
Days left to match	-0.0071***	-0.0427***	0.0400**	-0.0367***
	(0.0027)	(0.0107)	(0.0197)	(0.0106)
Days left to match squared	0.0004*	0.0023***	-0.0036**	0.0022***
	(0.0002)	(0.0009)	(0.0016)	(0.0007)
Number of competing offers	-0.0002***	-0.0016***	-0.0004	-0.0010***
	(0.0000)	(0.0002)	(0.0003)	(0.0002)
End of auction (dummies)				
Saturday	-0.0095	-0.0207	0.0152	-0.0222
	(0.0062)	(0.0239)	(0.0366)	(0.0154)
Sunday	-0.0102**	-0.0588***	-0.0194	-0.0480***
	(0.0046)	(0.0209)	(0.0328)	(0.0182)
Evening (6 to 10pm)	0.0022	-0.0379***	-0.0577**	-0.0069
	(0.0037)	(0.0136)	(0.0231)	(0.0079)
Ticket quality (base: top quality)				
Medium quality	-0.0078	0.1036***	0.0454	0.0575***
	(0.0050)	(0.0220)	(0.0409)	(0.0154)
Regular seats	-0.0041	0.2645***	0.2870***	0.1108***
	(0.0052)	(0.0182)	(0.0290)	(0.0186)
Number of offered tickets (base: 1)				
2 tickets	0.0058	0.1098***	0.0633	0.0551***
	(0.0053)	(0.0256)	(0.0421)	(0.0151)
3 or more tickets	-0.0086	0.0586***	0.0415	0.0322***
	(0.0071)	(0.0189)	(0.0424)	(0.0109)
Duration of posting (base: 3 days)				
5 days	0.0166***	0.0625***	0.0837***	0.0210**
	(0.0038)	(0.0165)	(0.0251)	(0.0093)
7 days	0.0206***	0.0974***	0.1009***	0.0306***
	(0.0040)	(0.0172)	(0.0290)	(0.0107)
10 days	0.0159***	0.1000***	0.0562	0.0508***
	(0.0041)	(0.0149)	(0.0420)	(0.0129)
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 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***
	(0.0093)	(0.0098)
Days left to match	-0.1102***	-0.0307
	(0.0229)	(0.0232)
Days left to match squared	0.0033	-0.0024
	(0.0020)	(0.0021)
Number of competing offers	-0.0050***	-0.0039***
	(0.0003)	(0.0003)
End of auction (dummies)		
Saturday	0.1076***	0.1329***
	(0.0413)	(0.0416)
Sunday	-0.0760***	-0.0465
	(0.0294)	(0.0290)
Evening (6 to 10pm)	-0.0553**	-0.0901***
	(0.0281)	(0.0279)
Ticket quality (base: top quality)		
Medium quality	0.7175***	0.6557***
	(0.0318)	(0.0320)
Regular seats	3.0046***	2.9657***
	(0.0409)	(0.0407)
Number of offered tickets (base: 1)		
2 tickets	0.3330***	0.3048***
	(0.0391)	(0.0385)
3 or more tickets	-0.0664	-0.0492
	(0.0568)	(0.0563)
Duration of posting (base: 3 days)		
5 days	0.3041***	0.2989***
	(0.0344)	(0.0335)
7 days	0.3544***	0.3713***
	(0.0355)	(0.0348)
10 days	0.4664***	0.4244***
	(0.0428)	(0.0430)
Intercept	0.2715	0.4520**
	(0.2073)	(0.1884)
Match Dummies	Yes	Yes
Observations	10,409	10,259

Estimations are OLS. Robust standard errors 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 Reserve Price.

	(1) All	(2) All	(3) Auctions only	(4) Posted Prices only
Auction (1=yes) (d)	0.2646***	-0.1226***		
	(0.0178)	(0.0154)		
ln Start Price		-0.4469***	-0.7548***	-0.2455***
		(0.0190)	(0.0493)	(0.0387)
Days left to match	-0.0674***	-0.0333***	0.0482**	-0.0367***
	(0.0139)	(0.0085)	(0.0242)	(0.0106)
Days left to match squared	0.0043***	0.0018***	-0.0043**	0.0022***
	(0.0012)	(0.0007)	(0.0019)	(0.0007)
Number of competing offers	-0.0014***	-0.0012***	-0.0004	-0.0010***
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
End of auction (dummies)				
Saturday	-0.0256	-0.0163	0.0184	-0.0222
	(0.0281)	(0.0188)	(0.0447)	(0.0154)
Sunday	-0.0941***	-0.0476***	-0.0234	-0.0480***
	(0.0244)	(0.0174)	(0.0396)	(0.0182)
Evening (6 to 10pm)	-0.0364**	-0.0302***	-0.0723**	-0.0069
	(0.0178)	(0.0110)	(0.0290)	(0.0079)
Ticket quality (base: top quality)				
Medium quality	-0.0016	0.0814***	0.0550	0.0575***
	(0.0259)	(0.0171)	(0.0498)	(0.0154)
Regular seats	-0.0277	0.1951***	0.3209***	0.1108***
	(0.0266)	(0.0132)	(0.0279)	(0.0186)
Number of offered tickets (base: 1)				
2 tickets	0.0282	0.0841***	0.0749	0.0551***
	(0.0264)	(0.0191)	(0.0487)	(0.0151)
3 or more tickets	-0.0141	0.0461***	0.0511	0.0322***
	(0.0311)	(0.0149)	(0.0530)	(0.0109)
Duration of posting (base: 3 days)				
5 days	0.0701***	0.0473***	0.1026***	0.0210**
	(0.0239)	(0.0125)	(0.0311)	(0.0093)
7 days	0.1102***	0.0722***	0.1225***	0.0306***
	(0.0243)	(0.0127)	(0.0348)	(0.0107)
10 days	0.0851***	0.0779***	0.0685	0.0508***
	(0.0263)	(0.0119)	(0.0520)	(0.0129)
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 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 Reserve Price.

Dep. Variable	(1) ESP	(2) ESP'
ln Start Price	-0.8003***	-0.7569***
	(0.0458)	(0.0476)
Days left to match	-0.1226	0.4513***
	(0.0789)	(0.0852)
Days left to match squared	0.0023	-0.0393***
	(0.0071)	(0.0082)
Number of competing offers	-0.0035***	0.0045***
	(0.0011)	(0.0012)
End of auction (dummies)		
Saturday	0.1411	0.4152***
	(0.1169)	(0.1235)
Sunday	-0.1325	0.1631
	(0.1039)	(0.1039)
Evening (6 to 10pm)	-0.0741	-0.2439***
	(0.0860)	(0.0884)
Ticket quality (base: top quality)		
Medium quality	0.3079***	-0.0965
	(0.1012)	(0.1056)
Regular seats	1.4411***	1.6234***
	(0.1391)	(0.1457)
Number of offered tickets (base: 1)		
2 tickets	0.3384***	-0.0311
	(0.1255)	(0.1189)
3 or more tickets	0.2034	-0.1156
	(0.1759)	(0.1706)
Duration of posting (base: 3 days)		
5 days	0.4028***	0.4620***
	(0.1235)	(0.1200)
7 days	0.2210*	0.3419***
	(0.1291)	(0.1243)
10 days	0.4010**	0.0779
	(0.1598)	(0.1587)
Intercept	0.4933	0.6262
	(0.7163)	(0.5392)
Match Dummies	Yes	Yes
Observations	1,190	1,170

Estimations are OLS. Robust standard errors 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**
	(0.0371)
Days left to match	-0.1138***
	(0.0218)
Days left to match squared	0.0040**
	(0.0019)
Number of competing offers	-0.0053***
	(0.0003)
End of auction (dummies)	
Saturday	0.0978**
	(0.0389)
Sunday	-0.0627**
	(0.0283)
Evening (6 to 10pm)	-0.0459*
	(0.0265)
Ticket quality (base: top quality)	
Medium quality	0.6071***
	(0.0301)
Regular seats	2.7241***
	(0.0385)
Number of offered tickets (base: 1)	
2 tickets	0.6549***
	(0.0365)
3 or more tickets	0.4918***
	(0.0525)
Duration of posting (base: 3 days)	
5 days	0.2845***
	(0.0323)
7 days	0.3552***
	(0.0336)
10 days	0.4615***
	(0.0408)
Intercept	2.5962***
	(0.1694)
Match Dummies	Yes
Observations	10,409

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

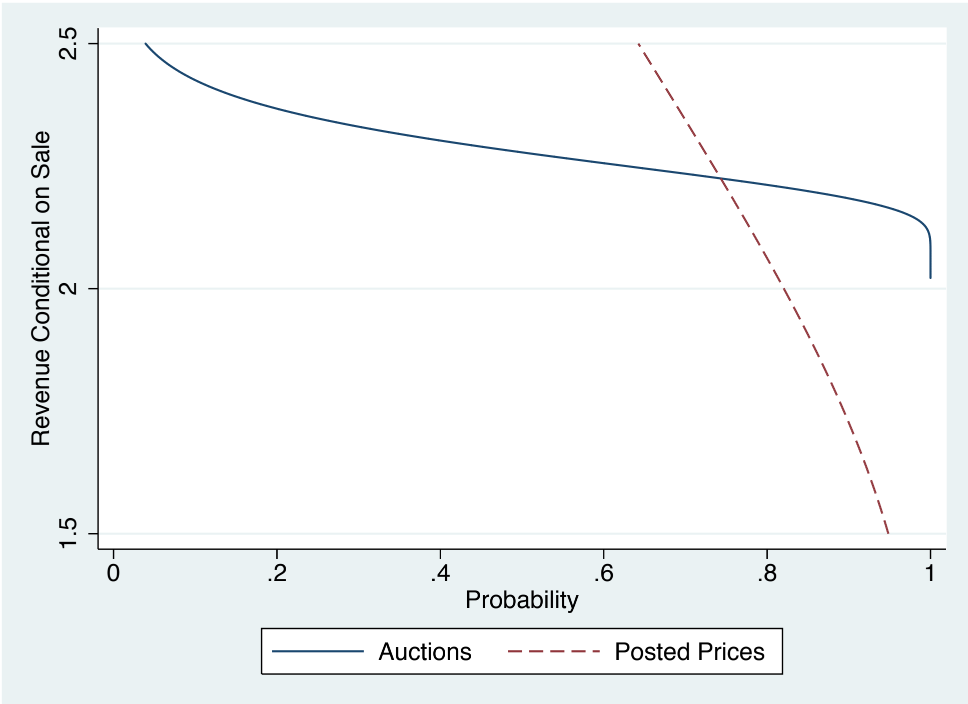

Figure 5: A (P, R)-plot derived from observed bidder behavior.

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Competing trade mechanisms and monotone mechanism choice

Abstract

We analyze mechanism choices of competing sellers with private valuations and show the existence of monotone pure strategy equilibria where sellerswith higher reservation value choose mechanisms with a lower selling probability and a larger revenue in case of trade. As an application we investigate the choice between posted prices and auctions and demonstrate that sellers refuse to offer posted prices as long as (risk-neutral) buyers do not differ with respect to their transaction costs in both trade institutions. If some buyers have lower transaction costs when trading at a osted price, it is optimal for sellers to offer posted prices if and only if they have a sufficiently high reservation value. We develop an econometric technique to compare the selling probabilities and revenues of posted prices and auctions and confirm our theoretical predictions with data from the EURO 2008 European Football Championship.

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