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Abstract

We use a unique hand collected data set of 6,258 auctions from the online football manager game Hattrick to study determinants and effects of reserve prices. We find that chosen reserve prices exhibit both very sophisticated and suboptimal behavior by the sellers. On the one hand, reserve prices are adjusted remarkably nuanced to the resulting sales price pattern. However, reserve prices are too clustered at zero and at multiples of € 50,000 as to be consistent with fully rational behavior. We recover the value distribution and simulate the loss in expected revenue from suboptimal reserve prices. Finally, we find evidence for the sunk cost fallacy as there is a substantial positive effect on the reserve price when the player has been acquired previously.

JEL Codes: D12, D44

Keywords: Reserve Price, Auction Revenue, Inattention, Price Clusters, Sunk Cost Fallacy

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1 Introduction

In a situation where buyers' willingness to pay is private information or the identity of the highest value buyer is unknown, an auction, instead of posting or negotiating a price, can be an efficient allocation mechanism. Hence, auctions have been used in a wide array of fields like art sale, real estate, or the allocation of spectrum rights. With the ascent of the internet, auctions have exceedingly gained popularity on platforms such as *eBay.com*, *amazon.com*, or *eBid.com*. Alone *eBay.com* is present in 39 markets and in 2007 approximately 84 million active users worldwide sold items on eBay trading platforms for nearly \$60 billion. I.e., *eBay.com* users worldwide trade more than \$1,900 worth of goods on the site every second.[1]

From various empirical, e.g. Lucking-Reiley (2000), or theoretical, e.g. Myerson (1981), Riley & Samuleson (1981), or Bulow & Roberts (1989), studies it is obvious that reserve prices (public minimum bids set by the seller) are an important strategic design element in most auction environments.[2] Using a hand-collected data set of 6,258 auctions of virtual football players traded in English auctions on *hattrick.org* we are able to address both positive as well as normative aspects of reserve price setting. We analyze how reserve prices are set and where they deviate from theoretically predicted patterns and in addition perform the counterfactual exercise and show how much expected revenue is actually foregone by setting suboptimal reserve prices.

The online game Hattrick (*HT*) is the world's largest online football (soccer) manager game with almost one million participants. Every day about 40,000 virtual players are traded on the *HT* transfer market. By design, these trades take place in a highly controlled environment including a standardized duration for each auction, a fixed mode of how players on sale are presented, and no risk of default. Sellers are however free to choose a non-negative reserve price. Unlike many other online auction platforms, in *HT* there is no relation between the minimum bid and the transaction fees a seller is charged, which could bias individuals in their choice of a reserve price. Moreover, when *HT* players are on the market, all relevant information concerning their quality becomes publicly available. That is, there is no information asymmetry between buyers and sellers and hence no scope for a winner's curse[3] and reserve prices contain no quality signal. Thus, for the bidders the auction takes place in a context where individual valuations are determined by idiosyncratic shocks to a common and publicly observable value. In Section 2 we describe the *HT* auction

[1] Source: http://news.ebay.com/about.cfm

[2] Rosenkranz & Schmitz (2007) extend the analysis to non-standard reference point dependent preferences and show whether and how reserve prices perceived as reference points affect bidding behavior.

[3] The winner's curse refers to the fact that the bidder with the highest estimate of quality is likely to hold a too positive view of the true but unobservable quality (common value), which then forms the basis of private valuations of the product.

market in detail and explain how success in the game crucially depends on profitably trading virtual players.

We are well aware that there may be reservations to working with data from a source like *HT*, which is clearly labeled as a game and where all financial transactions are carried out in terms of virtual money. However, success in the game requires patience and a long-term planning horizon and according to the developers, an individual manager typically keeps playing actively for about three years. Moreover, they also state that as many as 500,000 managers visit their account every single day. Above that, even though the basic access to the game is free of charge, roughly 20% of registered managers not only devote much of their time to the game, but they also voluntarily invest real money in *HT* by opting for a costly premium account.[4] These facts underpin our view, partially inferred from own introspection, that the *HT* managers are very ambitious and that the game provides rather strong incentives. Plausibly, the within-game motivation can be regarded as high as that present in laboratory experiments or small stake internet sales.[5] It thus seems reasonable to retrieve meaningful insights on individual behavior also for real life situations involving real money.

From the classic contributions to auction theory, e.g. Myerson (1981), Riley & Samuleson (1981), we know that the optimal reserve price in an independent private value environment is a continuous function of the hazard rate of the distribution of valuations of buyers and does not depend on the number of potential bidders. It is set such that the expected marginal revenue from a higher sales price equals the expected marginal cost from a higher risk of auction failure.[6] In the reserve price patterns in our data, we find both evidence for very sophisticated and boundedly rational behavior of sellers. We show that reserve prices are predicted, qualitatively and quantitatively, by the same observable characteristics that predict sales prices.

[4] "Supportership" enables a package of further features and tools like bookmarks and statistics at a fee of about $30 per year on a non-subscription basis. The managers take no technical advantage in their in-game performance from this supporter status, but it merely "*make[s] your time at* HATTRICK *easier as well as more fun*", as the operators of the game put it. (Source: http://www.hattrick.org/Help/Supporter/)

[5] Moreover, in a recent study Castronova (2008) provides suggestive evidence that economic constraints like the law of demand apply similarly in virtual environments with virtual money as they do in the real world.

[6] Levin & Smith (1994) and Levin & Smith (1996) analyze alternative models with endogenous (and costly) entry decisions prior to the bidding stage. In their setting, the number of bidders and the optimal reserve price actually covary, implying that under IPV small or no reserve prices are optimal as this attracts more bidders. Conversely, they argue that a positive reserve price is useful in reducing the number of bidders in a common value auction, since the winner's curse is the worse the more bidders are participating. However, in our *HT* environment costs of entry (bid preparation, information gathering) are negligible and hence we treat the number of bidders as exogenously given.

In particular, we find that *reserve prices exhibit the so-called "birthday effect"* that has been documented for the *HT* transfer market sales prices in Englmaier & Schmöller (2009): Though a player's value in the game decreases, ceteris paribus, continuously with his age measured in days as it becomes harder and harder to improve his skills by training, they show a very strong drop in sales prices just on a player's birthday. This indicates that buyers in *HT* give too much weight to the age of a player measured in years as opposed to his age measured in days, though the latter is also plainly visible to all buyers free of cost as can be seen in Figure 1. Our analysis shows that this birthday effect is also present with respect to reserve prices. Further examination of the data indicates that the presence of the birthday effect is not (only) due to the fact that sellers fall prey to the same information under-usage as the buyers, but because at least a substantial fraction of sellers tries to strategically exploit this bias of the demand side. We find a clustering of sale offers just before players' birthdays, indicating that sellers rationally want to sell players before they drop in value on their birthday. Furthermore, a sharp drop of median reserve prices immediately before the birthday indicates that sellers anticipate the immanent drop in market value. Hence, they want to make sure that the player is actually sold where a (too) high reserve price might endanger this.

We run hedonic regressions with the sales price and with the reserve price as dependent variables and identical sets of explanatory variables. As stated above, all of them have qualitatively similar effects – with one notable exception: we have a good proxy whether a player on the transfer market had been acquired by the seller previously or whether he was promoted (basically for free) from the seller's own youth team. We find that, ceteris paribus, sellers set *significantly higher reserve prices* (by about 23% of the mean) for players they have bought as compared to players they promoted internally. In contrast to that, *sales prices are significantly lower* (17% of the unconditional mean price) for previously traded players unconditional on a successful sale. In Section 3 we discuss in detail why the negative effect we observe in sales price patterns is what we would expect from rational actors. However, the positive reserve price premium we find for previously traded players is more in line with a *sunk cost fallacy*, for example due to loss aversion with respect to the previous selling price, leading to an entitlement effect.

Finally, we find that *reserve prices are too clustered* as to be compatible with fully rational behavior. In particular, the reserve price pattern spikes dramatically at multiples of €50,000, and also suggests a lower scale clustering at multiples of €5,000. Moreover, a large fraction of the sellers (18%) sets a reserve price of zero. We interpret this as evidence for sellers using a round number heuristic in determining reserve prices, thereby not setting the reserve price sufficiently fine tuned. We are able to do even more, as from observing the sales prices, in the English auction resembling the second highest bidder's valuation, we are able to estimate the underlying distributions of valuations, $F(v)$, calculate the optimal reserve prices given $F(v)$, and calculate the share of expected revenue lost at the actual levels as compared to the situation with optimal reserve prices.

With the rise of the internet, auction data are more readily available and hence these data have been widely used to study the effect of various elements of auction mechanisms. Lucking-Reiley (2000) presents data from a comprehensive study of 142 different internet auction sites and describes the transaction volumes, the types of auction mechanisms used, the types of goods auctioned, and the business models employed at the various sites. Bajari & Hortacsu (2003) go further in their analysis and show that in their sample of coin auctions on *eBay.com*, reserve prices are set below the book value of their coins. In contrast, we find that while many reserve prices are set very low (or even at zero), a substantial fraction is set very high. As we do, Bajari & Hortacsu (2003) estimate the value distribution $F(v)$ from the observed bids and use it to evaluate the effect of alternative reserve prices. However, they do not solve for the optimal reserve price as a benchmark as they cannot rule out common value elements in their data. The evidence on whether or not reserve prices are revenue enhancing is somewhat mixed. Ariely & Simonson (2003), Kamins et al. (2004), and Lucking-Reiley et al. (2007) show in field experiments that selling prices increase in the reserve price. Reiley (2006) documents evidence from a field experiment on ebay that reserve prices reduce the number of bidders, the probability of an actual sale, and the unconditional expected revenue. However, the expected revenue conditional on a sale increases. Bajari & Hortacsu (2003) and Hoppe & Sadrieh (2007) find in their field study and field experiment respectively no positive effects of reserve prices on selling prices. Finally, Simonsohn et al. (2008) take a different tack. They document that eBay bidders prefer auctions with more bids, hence sellers have an incentive to set low reserve prices. Of particular interest to us is the study by Trautmann & Traxler (2009), which also uses data from auctions of players in *HT*. Their focus is to separate two potential channels how reserve prices might affect selling prices: A reference point or anchoring effect as suggested in Rosenkranz & Schmitz (2007) and a standard rent appropriation effect that stems from reserve prices forcing the winning bidder to pay more than the second highest bidders valuation. Trautmann & Traxler (2009) find a positive effect of reserve prices but they find no evidence that any of these higher prices stem from a reference point effect but rather can be accounted for by rent appropriation.

The sunk cost fallacy, sometimes referred to as "irrational escalation of commitment", has been studied by psychologists for decades, e.g. Staw (1976), Arkes & Blumer (1985), or Bazerman (1986). In most recent discussions in economics, it has been related to prospect theory (Kahneman & Tversky, 1979), specifically to a reference point and loss aversion. In many contexts, the presence of a sunk cost fallacy implies entitlements. There is ample evidence for the entitlement effect and the resulting Willingness-to-Pay/Willingness-to-Accept gap in controlled experiments[7], though recent work by Plott & Zeiler (2005; 2007) is critical with respect to the validity of the endowment and entitlement effects outside the lab. Our study indicates a strong and persistent entitlement effect in a very competitive natural setting. All our results are robust if we control for the experience of the sellers in our sample. Genesove & Mayer (2001) analyze seller behavior in the Boston residential real estate market using proprietary panel data. Sellers whose condominium's expected selling price falls below the original purchase price due to an aggregate market downturn tend to set asking prices well above the expected price level. They argue that this unwillingness to accept market prices for property in the down part of the market cycle could stem from loss aversion on behalf of the sellers. However, in our sample there are no losses caused by business cycle swings, since all data was collected within only a fortnight. The setting studied in Genesove & Mayer (2001) involves bargaining, where the final price can fall below the initial asking price of the seller, which in addition not necessarily reflects his reserve price. It is also reasonable to assume that the evaluation of a condominium may involve substantial search costs, whereas all relevant information on *HT*'s virtual players is readily available, highly standardized, and thus easily comparable. Hence, while we observe similar behavior of sellers, the motivations behind it may differ considerably.

Clustering of stock prices at integers, i.e. that limit sell orders and also prices tend to be rounded to whole numbers rather than displaying fractions, has been documented by Niederhoffer (1965), Harris (1991), and Sonnemans (2006), who also provides an overview of related studies on price clustering in stock markets, discussing possible explanations. Benartzi & Thaler (2007) show that a round number heuristic seems to be important in determining savings choices, too.

The remainder of the paper is structured as follows. Section 2 describes the structure of the data and the relevant details of *HT*. Section 3 presents our empirical analysis and results. In Section 4 we estimate the share of expected revenue lost relative to the optimum and Section 5 concludes. An Appendix collects additional Tables and Figures.

[7] For references see e.g. Thaler (1980), Knetsch (1989), Hanemann (1991), Shogren et al. (1994), Casey (1995), or Carmon & Ariely (2000).

2 Data Description

2.1 Institutional Background about Hattrick

Hattrick, founded in 1997, is a browser-based free online football manager game with almost one million registered users, henceforth referred to as "managers".[8] The basic concept of the game is to manage your own virtual football club, which consists of virtual players that are represented by a multi-dimensional vector of attributes. A team plays at least one weekly game in a national league system against teams coached by other managers. In *HT*, a season, or an in-game year, lasts for 112 real-time days. The outcome of matches is determined by random simulation on the basis of the chosen strategies of the opponents, skills of the virtual players and other factors that determine the probabilities to win. The tasks for a manager to lead his team to success are numerous, ranging from decisions on match tactics and line-ups, over hiring team staff like doctors and co-trainers, over "drafting" a new player from the team's youth squad and either selling, keeping, or firing him as needed, to monitoring the team's training program. Many managers complete all of these tasks almost on a daily basis. announce The sportive aspect is but one of the supporting pillars of the game. Maintaining a virtual club requires the managers also to develop a solid financing scheme. The most important source of (in-game) revenue for a manager is successfully trading players on the *HT* transfer market. Most managers follow a "train and trade"-strategy which first ensures the improvement of quality of their own virtual players by choosing a training scheme and then profitably selling them to other managers. Since the proceeds from player sales are the major source of income in *HT*, the transfer market provides strong incentives for the participants in this open-ended manager game.

2.2 Goods: The Virtual Players

A virtual player is defined in about thirty dimensions. Figure 1 depicts the typical profile interface for a player, including the set of his attributes and the corresponding auction details. The most important attributes are the eight abilities displayed in the lower middle of the profile which we denote as his "skills".[9] While *stamina* and *set-pieces* are general skills, the remaining six - *playmaking, winger, scoring, keeping, passing,* and *defending* - determine a player's suitability to play in certain positions in the line-up. For instance, a player with his best skill being *keeping* is rationally classified as goalie. In the terminology of the game, skill

[8] We refer to human users as "managers", while using "player" to address virtual football players.

[9] To all other attributes, we will refer to as "characteristics". For a classification of the values each attribute can take, refer to Table 1.

levels are denoted as adjectives. To simplify the notation, we use integer values to address them, e.g. "passable" corresponds to score 6 of 20.[10]

Figure 1: Virtual Player Profile

Notes: Next to the player attributes, on the lower right all information regarding the auction details are displayed. The seller of this keeper set him on the transfer market during the evening on February 01, 2008 (i.e. exactly 72 hours before the deadline displayed) at a reserve price of € 25,000. (Source: www.hattrick.org)

From the set of player attributes, only these eight skills can be actively improved by training. However, it takes several weeks for an individual player to increase by a full skill level and only a single skill can be trained at a time. Hence, managers have to specialize in training only one specific skill, say *keeping*. As soon as such a keeper-trainee surpasses the threshold for a skill-up in this skill, the manager can profitably sell him to another manager and assign the free training slot to a new (and younger) trainee, which he can either acquire on the transfer market or promote directly from his own youth team.[11] The proceeds from the sales are in turn used to finance the club.

The value of a player crucially depends on two main factors, his current skill levels and his age. The first determine the strength a player adds to a team if he is currently lined-up in a certain position for a match. This is independent of a player's age. For the purpose of this paper, we refer to this component as his "Consumption Value" (CV). For instance, a keepers' CV is almost exclusively driven by the goalkeeping-skill. However, the second main channel of influence for the value of (young) players arises due to the fact that age is a key determinant for training effectiveness. In *HT*, the marginal skill-improvement from

[10]Table 7 in Appendix 6 shows the detailed ranking of the values for the skill levels, as it can also be found in the game's manual.

[11]Each manager can promote one player from the youth team each week, whose attributes are determined randomly with a high probability of low skill levels. Age is also randomly assigned on the interval 17 to 19 years. All descriptions of the game are based on the set of rules and institutions that were in place during the collection period of our data set.

training declines with the age of a player. The younger a player, the more he benefits ceteris paribus from training and the faster he advances to a higher skill level, which in turn increases his CV. As a consequence, a viable training strategy necessarily requires rather young players, since they have the highest innate potential for further skill development, or "Advancement Potential Value" (APV) as we label it. Importantly, the marginal effect of training is otherwise homogeneous for all virtual players, i.e. there exists nothing like a talent-attribute capturing the potential for skill-improvements. It does to some extent depend on the ability of the club's trainer, and the training intensity chosen by the manager, where the latter two give rise to variation in private valuations.

Ceteris paribus, a player who is just a few days younger than another should not be worth much more, since the difference in their APV is minimal. This holds true irrespectively of whether one already turned a year older while the other's birthday lies just ahead. Yet, in another dataset from *HT* Englmaier & Schmöller (2009) find that the observed sales price pattern exhibits strong discontinuities at the birthdays of the virtual players, which they refer to as the "birthday effect". The buyers overreact to the informational content of the age-group indicator *years*, while disregarding the finer information on a player's age attribute as conveyed through the *days*, even though the precise age of a player is explicitly stated in the form "X years and Y days" on his profile page (see Figure 1). Naturally, this raises the question of whether the reserve prices set by the sellers pick up the birthday effect, or whether sellers react strategically to the documented buyers' behavior. Along with the individual values they can take in the game, Table 1 provides an overview of the player attributes and other variables we employ for our analysis.[12]

Among the remaining characteristics, a player's *total skill index* (*tsi*), which represents a noisy measure for his overall abilities, is the one most likely to have a (positive) influence on market value. To see this, note that *HT* calculates the skill-levels as real numbers including hidden decimal places, the so-called "sub-skills", while the player profile only displays the adjective reflecting the current integer value for each skill. With each training a player receives, the trained skill increases by a marginal increment (which is declining in age), and so does the *tsi*. While also correlated to other attributes (e.g. *form*), the *tsi* score thus constitutes a noisy signal for the sub-skills of a player, i.e. for how close he is to reach the next higher level in one of his skills. Though a complete description of all characteristics is beyond the scope of this paper, for our empirical estimation we control for the full vector of attributes.

[12]In the following, we use italics to denote the variables from our sample.

Table 1: List of Variables

	Variable	Description	Range
Player attributes	years	Age in years (1 *HT*-year ≡ 112 real-time days)	17+
	days	Age in days (1 *HT*-day ≡ 1 real-time day)	{0,..,111}
	totalage	Precise age of a player in day units (normalized)	{0,..,335}
	days17-days20	Interaction term of days and age-group dummies	{0,..,111}
	form	Current form of player	{0,..,8}
	total skill index	Noisy indicator of overall quality of player	$\mathbb{N}_+$
	wage	Salary (exogenous; in virtual Euro)	$\mathbb{N}_+$
	keeper	Playing skill, position specific	{0,..,20}
	playmaking	Playing skill, position specific	{0,..,20}
	winger	Playing skill, position specific	{0,..,20}
	scoring	Playing skill, position specific	{0,..,20}
	passing	Playing skill, position specific	{0,..,20}
	defense	Playing skill, position specific	{0,..,20}
	setpieces	Playing skill for all player types	{0,..,20}
	stamina	Playing skill for all player types	{0,..,20}
	gentleness	High value if agreeable (ascending order)	{0,..,20}
	aggression	Low value if player aggressive (descending order)	{0,..,20}
	honesty	High value if honest (ascending order)	{0,..,20}
	plrexp	Experience of player	{0,..,20}
	ldrshp	Leadership qualities of player	{0,..,7}
Auction Data	askprice	Reservation price set by the seller	$\mathbb{N}_+$
	price	Auction end price paid by winning bidder	$\mathbb{N}_+$
	dtime	Time of deadline	hh.mm.ss
	dday	Day of deadline	dd.mm.yy
	sellerxp	Proxy for seller experience by relative country ranking	$[0-1]$
Dummy variables (1=yes, 0=no)	age17 - age19	Dummy for age-group	{0,1}
	peakhour	Did auction end during peak hour (5:30 p.m. - 10:00 p.m.)	{0,1}
	mon - sun	On which weekday did the auction end?	{0,1}
	acquired	Proxy for previous sale (player countryID = seller countryID)	{0,1}
	d_ask	Was the reserve price different from zero?	{0,1}
	d_sold	Was the player successfully sold?	{0,1}

2.3 Transactions: The Transfer Market

The transfer market in *HT* has a large trading volume with an average of about 40,000 players offered for sale each single day.[13] The selling mechanism implemented on the transfer market is an English ascending open bid auction. To sell a player, managers can specify a non-negative reserve price and submit an irreversible sell order by clicking a button. Each auction ends exactly 72 hours from submission, but the deadline is automatically extended by 3 minutes if a bid is placed within 3 minutes to the deadline. This continues until all bidders but one retire.[14] Importantly, all relevant information concerning a players quality - that is the full attribute vector - becomes publicly available once a player is offered on the transfer market. Hence, at the time of sale there is no information asymmetry between buyers and sellers and, for that matter, the econometrician.

[13]Source: http://www.databased.at/HT/htpe

[14]Given the reserve price is set below the second highest bidder's valuation, the transfer price will equal the second-highest bid plus one discrete increment, i.e. the format is strategically equivalent to a sealed-bid-second-price auction. For reference on the effects of the employed ending rule on bidding behavior see e.g. Roth & Ockenfels (2002) and Ariely et al. (2005).

Since all players on sale are displayed in the same standardized way as shown in Figure 1, the sellers have no possibility to affect the way how an individual player is presented to potential buyers. Except for the timing of the sell order, which determines the auction deadline, this leaves a seller with a single dimension of choice: The reserve price. Thus, we should expect that sellers give careful consideration to the utilization of this remaining instrument of potential influence on the auction outcome.

The transfer market provides a search tool, which allows the managers to filter for various player attributes like age-group, current bid, and up to four playing skills at desired levels. The inquiry returns a list of offered players matching the selected filter, where an abstract of their main characteristics is displayed (see Figures 10 and 11 in Appendix 6).

To submit a bid for a player, a prospective buyer manager must enter his profile. Each bid must at least be equal to the reserve price or above the current highest bid, respectively. Placed bids are binding and irreversible. After the auction ends, the player is automatically transferred to the winning manager's team and the seller receives the winning bid net of some small fee.[15] If a player received no bid, the auction fails and he stays with the seller.

2.4 Sample Selection and Data Description

Our main interest in this paper is to study the determinants and effects of reserve prices. For this purpose, we collected all publicly available information on 6,258 virtual players offered for sale on the *HT* transfer market between November 18, 2007 and December 02, 2007.[16] The sample considers the specific subgroup of keepers aged between seventeen - the youngest age possible in the game - and nineteen years, all with an identical *keeping*-skill of score 6 out of 20, i.e. "level-6 keepers". The age criterion is motivated by the facts that (i) the APV is most important at young ages and (ii) young players are heavily traded. Regarding the focus on keepers, note that the values of field player types depend not only a combination of several skills but also on other factors, e.g. the chosen match tactics. In effect, individual skills can receive quite different weights in the evaluations across managers, making it hard to measure the impact of a specific attribute on the price, or, as in our case, the reserve price. In contrast to that, for keepers by far the most influential skill unambiguously is the *keeping*-skill, which determines their value to the largest extent. By holding the keeping-skill constant at a score of 6, which accounts for the thickest market segment of players in this category, we effectively suppress the impact of variations in the skill-dependent CV on

[15]These transaction costs are negligibly small and do not affect any of our results.

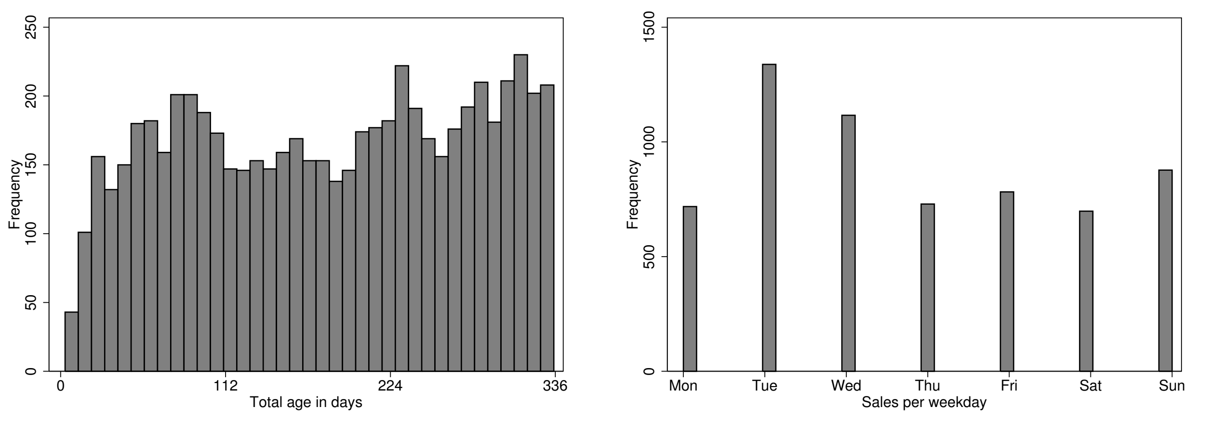
[16]From an initial sample of 6,460 players in the relevant skill- and age-group, we excluded 4 players that play for their respective home country's national team, 66 players with reserve prices identified as outliers by Grubbs' test (Grubbs, 1969) and 132 players that were injured at the time of the auction.

the observed reserve prices. We are thus able to identify influential factors for the players' APVs in the sample, which crucially depend on their age, or more precisely, their precise age including the days.[17]

Next to all relevant player and auction characteristics, we also collected information on the sellers. For a subsample of 2,411 auctions we are able to construct a proxy for seller experience ($sellerxp \in (0, 1]$), where we use the information on how a manager ranks relative to all other managers within a given country. We argue that a higher ranking within a country is a good indicator for being more experienced as it can only be achieved by playing the game for a long period of time and/or being very successful quickly, which should to a large degree be correlated with having routine playing the game.

Furthermore, we use the information whether a player plays abroad or not, indicated by a 20% bonus on his wage,[18] as a proxy whether he had been previously traded (*acquired* = 1), or whether he is a "fresh" player from the seller's own youth team (*acquired* = 0). Fresh players never receive this 20% playing-abroad bonus on their wages, as e.g. German teams always produce fresh German players. As in roughly 85% of all trades buyer and seller are not from the same country, our potential mistake from missing trades within a country is small and this 20% bonus is a good proxy to discriminate between fresh and previously traded players.

Figure 2: Distributions of Age and Sales



(a) Distribution of total age

(b) Distribution of sales per weekday

Figure 2a depicts the age distribution for the players in our sample, indicating a roughly balanced distribution for *days* within each age-group. The distribution of sales per weekday is shown in Figure 2b. On Tuesdays and Wednesdays we observe spikes in the number of

[17]The motivation for these selection criteria follows the lines of Englmaier & Schmöller (2009). Though many variables appear in both datasets, the present sample differs from theirs in some respects. In particular, we additionally collected records of the reserve prices and more details on the individual sellers.

[18]Note that a player's wage is exogenously fixed by HT and cannot be influenced by the managers.

sold players. The reason for this is that new players can be "drafted" each Saturday after an weekly update and often are immediately offered for sale, which explains the number of deadlines expiring on Tuesdays and Wednesdays being accordingly higher. In our regressions, we use dummies (*mon-sun*) to control for possible effects of the auction end day and additionally also include a dummy (*peakhour*) to indicate whether a player was sold between 5:30 p.m. and 10 p.m., where the highest numbers of simultaneous online users are reached and most auctions expire.[19]

Table 2 states the summary statistics of the most important variables in our sample. As shown in Panel A, the mean reserve price (*askprice*) in our sample was €77,537, but levels as high as €579,000 were reached.[20] Note that the final prices fall into a comparable range, indicating that by and large the reserve prices were not set beside the point. Since the age of a player is displayed in the form "X years and Y days" on his profile-page, the variable *years* defines his age-group and *days* discloses information on his precise age, or equivalently, the distance to his next birthday. The constructed measure $totalage \in [3, 335]$ displays the total age of a player in day units and thus combines the information contained in both age variables, where we normalize $totalage \equiv 112{\cdot}(years - 17) + days$, using the fact that a year in HT is normalized to 112 days.[21]

Table 2: Summary Statistics

Panel A.				Panel B.			
Variable	Mean	Min	Max		Variable Value	Frequency	Percent
askprice	77,537	0	579,000	age distribution	(years = 17)	1,886	30.14
price[a]	81,459	0	634,000		(years = 18)	1,935	30.92
years	18	17	19		(years = 19)	2,437	38.94
days	59	0	111				
totalage[b]	181	3	335	fresh players	(acquired = 0)	4,253	67.96
total skill index	1,994	650	3,240	purchased players	(acquired = 1)	2,005	32.04
wage	1,884	770	2,676				
form	6	1	8	reserve price	(askprice > 0)	5,108	81.62
stamina	3	1	9	no reserve price	(askprice = 0)	1,150	18.38
passing	1	1	4				
playmaking	1	1	3	successful trades	(price > 0)	4,743	75.79
scoring	1	1	3	players unsold	(price = 0)	1,515	24.21
winger	1	1	4				
setpieces	2	1	7	sold at reserve price	(price=askprice)	756	15.94
defense	1	1	4	sold above reserve price	(price>askprice)	3,987	84.06

a. A Price of zero indicates a failed auction. The minimum price among all successful trades was €19,000.
b. The variable $totalage = 112 \cdot (years - 17) + days$ displays a players precise age in day units. The minimum value of *totalage* at 3 reflects age "17 years and 3 days" and the maximum value at 335 equals "19 years and 111 days".

Panel B provides some frequency statistics of our data. Note that all age-groups are roughly equally represented, with a slight majority of players aged nineteen. According to our wage-bonus proxy (indicated by the dummy *acquired*), in 32% of all auctions the sellers offered

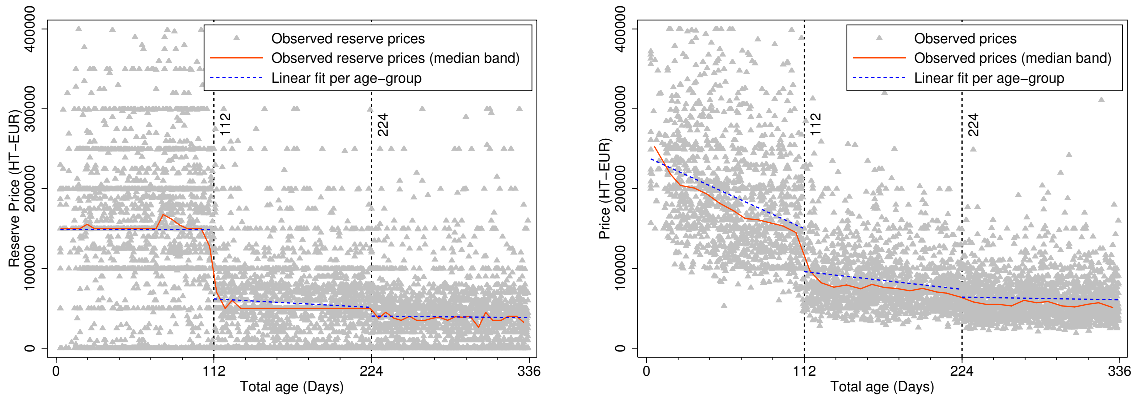
[19]See Figure 9 in Appendix 6.
[20]All monetary values are denoted in units of virtual HT-Euros.
[21]Note that since each auction lasts for 3 days, *totalage* has its minimum at 3, or "17 years 3 days". The maximum value of *totalage* at 335 reflects the age "19 years 111 days".

players they previously bought themselves on the market. 68% of the times, a player promoted from the own youth squad of the seller, i.e. a "fresh" player, was auctioned off. For 5,108 players in our sample the seller fixed a strictly positive reserve price. Surprisingly, this fact already establishes that more than 18% of the sellers did not make use of the possibility to set a reserve price.[22] Of all players, 4,743 were sold and in 756 cases the trade took place at a price equal to the minimum bid (single bidder case).

3 Analysis and Results

In light of the "birthday effect" on the demand side of *HT*'s transfer market, which is illustrated in Figure 3b analogously to Englmaier & Schmöller (2009) for the present sample, it seems a natural point to start our analysis of the driving forces in the formation of reserve prices by examining their relation to a player's age.

Figure 3: Relation of Reserve Prices and Sales Prices to Total Age



(a) Pattern of Reserve Prices

(b) Pattern of Sales Prices

Notes: The dashed lines at 112 and 224 mark the points where the players turn eighteen and nineteen, respectively.

Intuitively, the variable *totalage* captures all available information on the players' age attribute. As we argue above, and as implied by the nature of the game's training algorithm, the value of a player should ceteris paribus decline continuously as *totalage* increases. This fact should also be reflected in the reserve prices.

However, Figure 3a already reveals that the relation between reserve price and total age is not smooth but exhibits large discontinuities where the players enter the next higher age-group, indicating that the birthday effect also persists for reserve prices. Since most managers in *HT* alternate between both roles, it does not seem too surprising to find similar behavioral

[22] In line with Simonsohn et al. (2008), it is possible that these managers may want to maximize entry and the number of bidders in the auction by not screening out any low-value bidders. As we will show in Section 4, however, in terms of expected auction revenue they forego potential profits.

patterns for buyers and sellers. At a first glance, it stands to reason that also the sellers are inattentive to the finer information on the age attribute as conveyed through the *days* of age. Another possibility is that the bias on the demand side actually triggers the observed choice of reserve prices, and what we observe is the result of at least some sellers following strategic considerations and trying to exploit the biased bidding behavior.

Even more intriguing, reserve prices appear to react even less sensitively to the precise age of players than the sales prices. The pattern depicted in Figure 3a reveals substantial clusters at 0 and at multiples of €50,000. As we discuss in more detail below, this indicates that reserve prices are too clustered as to be compatible with fully rational behavior, where the optimal reserve price is a continuous function of the hazard rate of the distribution of buyers' valuations (see e.g. Krishna, 2002). If that was the case, at any age the reserve prices should be similarly dispersed as the final sales prices (see Figure 3b).

In the following, we analyze these indications in more detail. After a brief discussion of the estimation model, we present the results from a hedonic regression analysis that allows us to identify the determinants of the reserve price from the set of attributes and the auction details in our data. In addition, we also examine possible interactions between the observed demand and supply side behavior.

3.1 Estimation Model and Predictions

If a seller wants to maximize his expected revenue, his choice for the reserve price for a player rationally requires him to form an estimate of the expected bidders valuations. Since both parties, buyers and sellers, share the same information set on the players' attributes when pursuing their evaluation task, our intuition is that similar to the bidders' valuations, also the reserve price is a function of the various player attributes.

To put more structure on the estimation model, consider Figure 3a again. Note that the observed discontinuities where the players turn one year older apparently differ in their relative size. To account for this possibility, we decompose the variable *years* into dummies for each age-group, which we label *age17, age18,* and *age19.* For example, the effect of age-group eighteen is measured by *age18* taking value 1 and 0 otherwise. Since these dummies are perfectly correlated, we need to include only two of them in our estimation model. As we drop *age17* from the regression, the resulting coefficients for the included dummies are to be interpreted as the difference in values upon entering an age-group relative to the price of a player aged "17 years 0 days". Moreover, we account for the impact of a marginal day of age separately for each age-group by interacting the age-group dummies with *days*, which yields the variables *days17, days18,* and *days19* $\in [0, 111]$. They display the days of age conditional on belonging to the specified age-group and zero otherwise. Formally, this corresponds to a piece-wise linear relationship between *totalage* and *askprice.*[23] All other regressors are assumed to enter linearly into the regression model, which is thus given by

$$\begin{aligned} askprice \;=\; \alpha \;&+\; \beta_{age18} \cdot age18 + \beta_{age19} \cdot age19 + \\ &+\; \beta_{day17} \cdot days17 + \beta_{day18} \cdot days18 + \beta_{day19} \cdot days19 + \\ &+\; \beta_{tsi} \cdot tsi + \beta_{acquired} \cdot acquired + \delta \mathbf{X} + u, \end{aligned} \tag{1}$$

where $\mathbf{X}$ represents the vector of all other attributes and auction details. With this specification, we are able to identify and measure the average magnitude of potential discontinuities in the reserve price pattern at the players' birthdays. Intuitively, the coefficients for the age-groups (β_{age18} and β_{age19}) reflect the total value difference *across* two subsequent age-groups, while the 112 times the respective impact of a marginal day (β_{day17}, β_{day18}, or β_{day19}, respectively) accounts for the aggregated value decline *within* an age-group. Only if both measures imply the same average decline, the reserve prices evolve continuously in *totalage.* Formally, this corresponds to the testable predictions stated in Hypothesis 1.

Hypothesis 1 *If the reserve price pattern exhibits the birthday effect, then*

(i) the coefficient for age18 *is larger than the aggregated value decline per day in age-group seventeen, i.e*

$$|\beta_{age18}| \;>\; 112 \cdot |\beta_{day17}|,$$

(ii) the difference between the coefficients of age19 *and* age18 *is larger than the aggregated value decline per day in age-group eighteen, i.e*

$$|\beta_{age19} - \beta_{age18}| \;>\; 112 \cdot |\beta_{day18}|.$$

The model specification (1) also includes the dummy *acquired* to control for possible differences between fresh players and those that have been traded previously. One might be tempted to argue that this should have no effect on the buyers' valuations and therefore should play no role for the sellers' considerations with respect to the reserve price.

However, whether or not a player was sold before conveys a subtle piece of potentially valuable information. To see this, recall from the discussion of *tsi* in Section 2 that the skill-levels contain hidden decimal places, while the profile page only shows the adjective corresponding to the integer value for each skill. For example, consider a freshly promoted player (*acquired = 0*) from a manager's youth squad, who displays a *keeping* score of 6.

[23] This specification is adopted analogously from the earlier analysis of the demand side of *HT*'s transfer market and corresponds to the information given to us by the makers of *HT*. For a more detailed discussion see Englmaier & Schmöller (2009).

Since skills are completely randomly assigned, his precise skill can take any value within the real interval $[6, 7]$. If we suppose that his sub-skill is uniformly distributed on this interval, a rational buyer would have a prior of 6.5 for the expected *keeping*-skill level.

In contrast to that, if a level-6 keeper was traded previously (*acquired = 1*), there is a positive probability that he was trained in *keeping* and just reached the lower threshold of 6.00 to display a score of 6. Recalling the "train-and-trade" strategy the majority of managers pursues, from perspective of the seller this would be the rational time to offer the player for sale. According to Bayes' rule, a rational prospective buyer should adjust his prior of the expected skill-level, and thus his value estimate for such a player, downwards accordingly.[24] Since an optimal reserve price depends on the distribution of the bidder's valuations, if anything, this implies that the reserve prices should not be larger for purchased players relative to fresh ones.

Hypothesis 2 *If the sellers correctly anticipate the considerations of the buyers with respect to a previous sale, the reserve prices for purchased players should not be larger than those for fresh players, i.e.*

$$\beta_{acquired} \leq 0.$$

3.2 Results

To test the validity of the above hypotheses, we start out with a series of hedonic OLS regressions with the reserve price as the dependent variable, where we only consider observations where the managers set a reserve price different from zero.[25] We either include only the main variables of interest or the full set of controls. In addition, we run a separate regression for experienced managers to see whether they behave differently than the average manager, where we classify a seller as an expert, if his team is ranked among the top 20% in his country (*sellerxp* < 0.2).[26] Moreover, to identify whether the reserve prices follow a similar pattern as the bidders valuations, we additionally run two regressions for the final sales price as the dependent variable, where the first contains all successful trades and the second only those, where the reserve price was set to zero. Table 3 presents the results.

[24] Since at present about 10% of the *HT* population trains *keeping*, the expected skill for level-6 keeper accordingly reduces to $0.1 \cdot 6.0 + 0.9 \cdot 6.5 = 6.45 < 6.5$

[25] All results remain qualitatively robust if we instead run a Tobit regression accounting for our sample being left-censored at zero. Moreover, the same holds true if we consider log-linearized reserve price records and control for influential outliers using a robust regression procedure. For the sake of brevity, here we omit the regression tables but they are available from the authors upon request.

[26] Using *sellerxp* < 0.2 leaves us with a bit less than 30% of the observations from the subsample where we were able to construct the experience dummy.

Table 3: Determinants of Reserve Price and Final Price (OLS)

	Reserve Price (Dep.Var.: *askprice*)			Sales Price (Dep.Var.: *price*> 0)	
	I	II	III (Experts)	IV	V ($askprice = 0$)
days17	-155.3**	-166.94**	-188.39	-1117.71***	-1201.36***
	(70.62)	(70.13)	(179.36)	(65.82)	(151.61)
days18	-101.61***	-99.53***	-161.14	-166.95***	-133.75***
	(37.67)	(37.36)	(104.12)	(25.19)	(41.51)
days19	-37.68	-33.89	-114.01	-30.38	-6.47
	(27.48)	(27.70)	(84.85)	(19.14)	(31.16)
age18	-103154.72***	-105770.16***	-107809.34***	-175188.98***	-174963.87***
	(5648.10)	(5650.93)	(15232.99)	(5114.74)	(11906.80)
age19	-127305.85***	-129555.76***	-134111.3***	-205895.9***	-203476.81***
	(5342.31)	(5466.74)	(14944.07)	(5064.23)	(12023.98)
tsi	31.91***	28.41***	15.59	70.6***	62.83***
	(2.29)	(4.73)	(16.37)	(3.93)	(6.68)
acquired	26590.64***	17617.9***	23255.22**	1549.44	-7125.8
	(1924.51)	(2940.95)	(10404.38)	(2168.67)	(4530.93)
Intercept	107024.18***	98755.29***	105784.1**	122811.82***	146496.82***
	(6537.69)	(14783.43)	(42967.33)	(12407.64)	(19927.25)
skills	no	yes	yes	yes	yes
character	no	yes	yes	yes	yes
daytime	no	yes	yes	yes	yes
weekday	no	yes	yes	yes	yes
R^2	0.47	0.48	0.56	0.74	0.74
N	5108	5108	567	4743	1149
F	453.10	120.72	29.15	244.52	48.03

Notes: Robust standard errors are stated in parentheses. Asterisks denote statistical significance at the 1%(***), 5%(**) or 10%(*) level. "Skills" captures the playing abilities except of *keeping* (= constant). "Character" contains all other player attributes except *tsi*. "Daytime" and "weekday" indicate whether dummies for daytime and day of the week were included.

The birthday-effect. In any reserve price regression (columns I-III), the age of a player has a highly significant negative impact on the level of the minimum bid set by the sellers. Representatively focus on the full-control specification in column II. The coefficient of *age18* indicates that the average reserve price for a player who just turned eighteen is substantially lower (by €105,770) than that for a player aged "17 years 0 days" at 99%-significant t-statistics, which is not too surprising given the game's training algorithm. However, holding all other variables constant, a marginal day within the age-group seventeen just accounts for a decline of €167 in the average reserve price. Aggregated over the whole year (112 days), this gradual day-by-day decline explains only 18% (€18,704) of the total value loss measured on the eighteenth birthday of a player. More precisely, the remaining 82% of the total decline establish an enormous discontinuity in the reserve price pattern where a player turns eighteen, i.e. $|\beta_{age18}| \gg 112 \cdot |\beta_{days17}|$. A Wald-test shows that this difference is significant on the highest level (p-value: 0.000). Similarly, also at the nineteenth birthday of a player we find a significant discontinuity of 53% of the total decline between the age-groups eighteen and nineteen, and thus $|\beta_{age19} - \beta_{age18}| \gg 112 \cdot |\beta_{days18}|$.

In the regression for experienced sellers (column III), observe that the impact of a marginal day is qualitatively similar but no longer significant, which may be due to the reduced number of observations (N=567). Note that this implies that the reserve prices do not adjust to age *within* but only *across* age-groups, making our result even stronger. If we account for the aggregate day effects despite their insignificance, we find a discontinuity of 80% and 31% at the eighteenth and nineteenth birthday, respectively. The results from the regression analysis are thus consistent with the prediction from Hypothesis 1 that the reserve price pattern picks up the birthday effect, which establishes our first result.

Result 1 (The birthday effect): *Similar to the sales prices, the reserve price pattern does not evolve continuously in the total age of a player. Instead, it picks up the birthday effect in form of substantial and highly significant discontinuities at the players' birthdays.*

Reserve price and bidder valuation. Observe further that adding the full set of controls to the regression (column II) only slightly improves the predictive power of the estimation model relative to column I, implying that the age variables, *tsi*, and *acquired* are indeed the most influential factors for the choice of the reserve price.[27] Moreover, except for *acquired*, all coefficients in the reserve price regressions qualitatively mirror those for the sales prices in columns IV and V.[28] This is in line with the prediction that sellers take into account the bidders' valuations when forming their reserve price.

To distinguish whether the supply side reacts to the demand side behavior or vice versa, in column V we only consider the sales prices from auctions where the seller set no reserve price (*askprice* = 0). If the birthday effect persists also for this subsample, we can rule out that the latter originates from the supply side of the transfer market. As it turns out, this is indeed the case. We find clear evidence for a birthday effect in the sales prices in column V, amounting to highly significant discontinuities of 23% and 47% of the total decline at the eighteenth and nineteenth birthday, respectively.[29] Since the bidding pattern is thus qualitatively unaltered in absence of a positive reserve price, this implies that the sellers take into account the expected bidders' valuations when making their reserve price choice, yielding our second result.

Result 2 (Reserve prices relate to bidder valuations): *The reserve prices are shaped remarkably similar to the final prices and share the same subset of influential player*

[27]While each group of controls turns out to be jointly significant, all effects of individually significant control variables are of secondary order and do not conflict with any of our results. To ease the exposition, we therefore omit a detailed discussion. The full regression tables can be requested from the authors.

[28]Note however that the relevant coefficients in the price regressions are quantitatively much larger as in those for the reserve price and the latter does not react as nuancedly to the precise age. As we will discuss below, this likely is due to the strong clustering of the reserve prices.

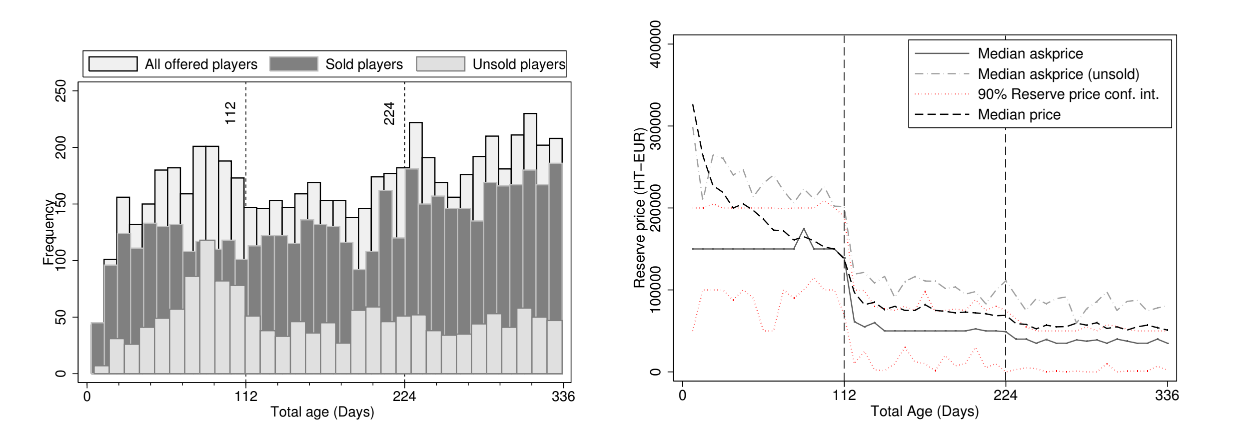
[29]The discontinuities for the full sample of non-zero sales prices can be readily calculated from column IV in Table 3 and are given by 29% ($\frac{\beta_{age18}-112\cdot\beta_{day17}}{\beta_{age18}}$) and 39% ($\frac{\beta_{age19}-\beta_{age18}-112\cdot\beta day18}{\beta_{age19}-\beta_{age18}}$), respectively.

attributes. The finding of a birthday effect for the supply side is consistent with the sellers relating their choice of the reserve price to the bidders' valuations.

Reserve price and auction outcome. Before we go on with our analysis of seller behavior, we briefly consider the predicted effects of a reserve price on the final price on a more general level. Relative to a zero minimum bid, one of the most basic general predictions is that higher reserve prices should reduce the likelihood of a successful sale, because low-value bidders will cease to participate (Reiley, 2006). Since all but one of the 24% failed auctions in our sample exhibited a strictly positive minimum bid, this prediction is clearly met.[30] A non-parametric Wilcoxon-Mann-Whitney (WMW) ranksum test confirms that the askprices for unsold players are significantly higher than those for successful trades (p-value: 0.000). We also find that the expected final price unconditional on a successful sale is lower if the reserve price is above zero (p-value: 0.000).

Evidence for sophisticated seller behavior. Conditional on a successful sale, however, the expected price is larger for positive askprices (p-value: 0.000). Intuitively, if the seller manages to set a reserve price between the highest bidder's and the second highest bidder's valuation, the auction price is mechanically higher than if there was no minimum bid and the seller successfully reaps some of the winner's surplus.[31] Since in 15.9% of the successful trades there was only a single bidder and the winning bid equaled the reserve price (Panel B of Table 2), we take it that the sellers in these 756 auctions were successful in their attempt to appropriate some of the highest bidder's surplus.

Figure 4: Distribution of Sold and Unsold Players and Median Reserve Prices



(a) Sold and Unsold Players by Age

(b) Mean Reserve Price by Age

Notes: The dashed lines at 112 and 224 mark the points where the players turn eighteen and nineteen, respectively.

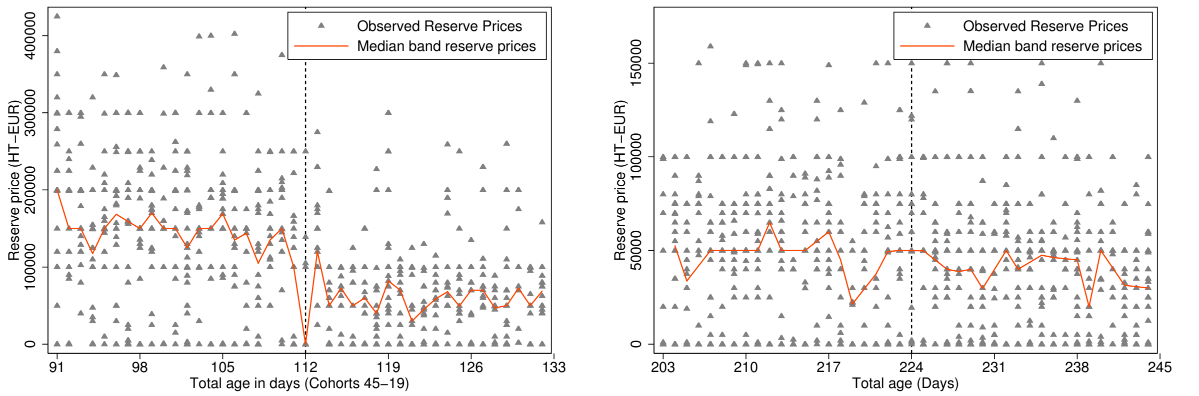
[30]Since the sample was hand-collected, this one observation may be due to a data-entry error.

[31]See also Trautmann and Traxler (2008), who - also in *HT* data - distinguish between this mechanical effect of "surplus appropriation" and a potential psychological channel of influence of the reserve price on the final price, as suggested in Rosenkranz & Schmitz (2007).

A natural next step is to ask whether at least some sellers react strategically in anticipation of the biased bidding behavior on the demand side of the transfer market. We would expect that sellers who are aware of the "birthday effect" should rationally try to sell players that are close to turn one year older, thereby avoiding to bear the accompanying value loss themselves. Consistent with this intuition, the distribution for sold and unsold players shown in Figure 4a clearly indicates an increased number of sale offers shortly before players turn eighteen. At about 90 days of total age, both the total number of offers and the number of failed auctions increase substantially, while the number of sales (and also the selling price pattern) remains largely constant. At the same time, the median askprice exhibits a local peak at exactly the same age level (Figure 4b). Though considerably less pronounced, we observe an similar increase around three weeks before the nineteenth and also the twentieth birthday.

Our intuition is that the sellers set rather high reserve prices at that stage in the hope to find a buyer who is not aware of the birthday effect and is thus willing to pay the asked price. Clearly, the downside of this strategy is that the probability for a successful sale is considerably reduced. This would also explain the higher number of failed auctions we observe. In even closer proximity to a player's birthday, however, a seller should rationally change his strategy and try to maximize the probability for a successful sale by charging a rather low minimum bid.

Figure 5: Reserve Prices in Close Proximity to Discontinuity Point



(a) Eighteenth Birthday (at 112) (b) Nineteenth Birthday (at 224)

Notes: The figure includes 756 (883) observations of players 3 weeks before and after their eighteenth (nineteenth) birthday.

Figure 5 plots the reserve prices closely before and after the eighteenth (nineteenth) birthday of the players in our sample. Consistent with our intuition, observe that the median reserve price for seventeen year old players begins to decline at 110 days of total age and drops to zero at 112, while it moves upwards again immediately after the birthday. A similar effect exists for the nineteenth birthday, though the drop is not as emphasized and takes place a few days before the birthday.[32] Though merely inferred by inspection, we take these observations as an indication that at least some sellers behave strategically.

Result 3 (Strategic seller behavior): *At least some sellers show sophisticated strategic considerations in their choice of the reserve price, as indicated by an increased number of sale offers and low minimum bids in close proximity to the birthdays. Moreover, a substantial fraction of sellers manages to extract additional rents from the winning bidder by setting a reserve price above the second highest bidder's valuation.*

The impact of a previous sale. Next, we consider the impact on the reserve price if a player was previously traded. Returning to Table 3, we find strong evidence that sellers set significantly higher minimum bids for players they acquired on the market ($acquired = 1$) relative to fresh players from their own youth squads ($acquired = 0$). Throughout all reserve price specifications (columns I-III), contrasting with Hypothesis 2 the coefficient $\beta_{acquired}$ is positive, large, and significant on the highest level, implying a strong positive correlation of *acquired* with *askprice*. Holding all other variables constant, the average reserve price for purchased players in column II exceeds that for fresh players by an amount of €17,618, or 23% of the mean reserve price. To illustrate the economic significance of this effect, note that the statistically weighted average impact of *tsi*, which we obtain by multiplying its coefficient ($\beta_{tsi} = 28.4$) times one standard deviation of the average *tsi*-score ($\sigma_{tsi} = 428$), only amounts to €12,155, i.e. about two-thirds of the coefficient for the dummy *acquired*.

In contrast to that, the regression for *price* conditional on sale in (column IV) yields an insignificant coefficient for *acquired*, all else equal implying that the buyers' valuations do not significantly differ whether or not a seller was traded before. Furthermore, in the specification for auction prices with a zero reserve price (column V), the coefficient for *acquired* is sizeable and has a negative sign, i.e. qualitatively the effect goes into the opposite direction for buyers. Though not statistically significant, this points towards the latter on average having a higher willingness to pay for fresh players, which is consistent with our above reasoning that a previous sale rationally translates into a lower expected (sub-) skill-level.[33]

An immediate implication of these results is that auctions for purchased players are ceteris paribus more likely to fail. Among the players that were bought ($acquired = 1$), the share of failed auctions was 32.6%, which is substantially higher than that for fresh players at 20.3%.

[32] However, note that the absolute impact of the birthday effect is considerably lower at age nineteen, which might explain the reduced reaction of the sellers at this point.

[33] Table 8 in Appendix 6 shows the results from an additional Tobit regression, where we include also the failed auctions with a zero sales price, i.e. with the sales price unconditional on entry as the dependent variable. In this approach, *acquired* has a highly significant negative coefficient ($\beta^{tobit}_{acquired} = -13,579$) which accounts for roughly 17% of the unconditional mean price. Unconditional on a successful sale, the average sales price is thus considerably lower for previously traded players.

A Pearson's chi-square test confirms that there is a statistically significant relationship between *acquired* and the frequency of players remaining unsold (p-value: 0.000). Moreover, if a player was previously traded, we find that in only 9.9% of the cases the reserve price was set to zero. Among fresh players with 22.4% this share is more than twice as large. To further substantiate this finding, we estimate the likelihood for a positive reserve price in a series of Logit regressions on the dummy *d_ask*, which takes the values 1 or 0 depending on whether or not there was a positive minimum bid. The results are shown in Table 4.

Table 4: Likelihood of Non-Zero Reserve Price

	Logit I		Logit II		Logit III expert sellers	
Dep.Var.: *d_ask*	Odds Rt.	Marg. Efct.	Odds Rt.	Marg. Efct.	Odds Rt.	Marg. Efct.
days17	1.0032	0.0005	1.0029	0.0004	0.9969	-0.0005
	(0.0024)		(0.0024)		(0.0059)	
days18	0.9980	-0.0003	0.9976	-0.0003	0.9991	-0.0001
	(0.0018)		(0.0018)		(0.0047)	
days19	0.9983	-0.0002	0.9980	-0.0003	0.9978	-0.0004
	(0.0015)		(0.0015)		(0.0044)	
age18	0.8622	-0.0211	0.8516	-0.0223	0.4291	-0.1368
	(0.1726)		(0.1727)		(0.2232)	
age19	0.7563	-0.0397	0.7673	-0.0368	0.4271	-0.1376
	(0.1434)		(0.1495)		(0.2231)	
tsi	0.9999*	0.0000	0.9998	0.0000	1.0007	0.0001
	(0.0001)		(0.0002)		(0.0006)	
acquired	2.4449***	0.1270	1.8536***	0.0857	4.7540***	0.2521
	(0.2101)		(0.227)		(2.2669)	
skills	no		yes		yes	
character	no		yes		yes	
daytime	no		yes		yes	
weekday	no		yes		yes	
LR Chi	212.93		306.42		95.04	
N	6258		6258		748	

Notes: The Logit procedure estimates the impact of the independent variables on the probability to observe "*d_ask* = 1" relative to "*d_ask* = 0". For each specification, the left (right) column states the odds ratio (marginal effect) for the respective regressor variable. Standard errors are stated in parentheses. Asterisks denote statistical significance at the 1%(***), 5%(**) or 10%(*) level. Sellers are classified as experts if *sellerxp*<0.2.

The first two columns (Logit I) show the odds ratios (exponentiated coefficients) and the corresponding marginal effects (instantaneous change) in the probability when only the main variables are used as regressors. Note that *acquired* is the only variable which has a highly significant impact. For a purchased player, the odds for a strictly positive reserve price (versus a zero reserve price) increases by a highly significant factor of 2.4 as compared to a player that was internally promoted from a seller's own youth squad. In terms of the marginal effect, a non-zero reserve price is 12.7% more likely for previously acquired players.[34] If we employ the full vector of player attributes and auction details as controls (Logit II), all results remain qualitatively robust. In line with our previous results, the same holds true in

[34]The marginal change equals the partial derivative of the predicted probability with respect to the respective regressor variable.

the separate regression for expert sellers (Logit III). If anything, the effect seems to be even more pronounced for experts.

Hence, if a player was bought rather than promoted internally by the seller, not only the level of the reserve price is higher on average, but also the likelihood that it is set different from zero at all. Stated differently, even though the managers interact in a highly competitive market environment, our findings indicate that the sellers in *HT* exhibit some form of sunk cost fallacy resulting in an entitlement effect with respect to players that they acquired on the market, but not for those promoted from their own youth squad.

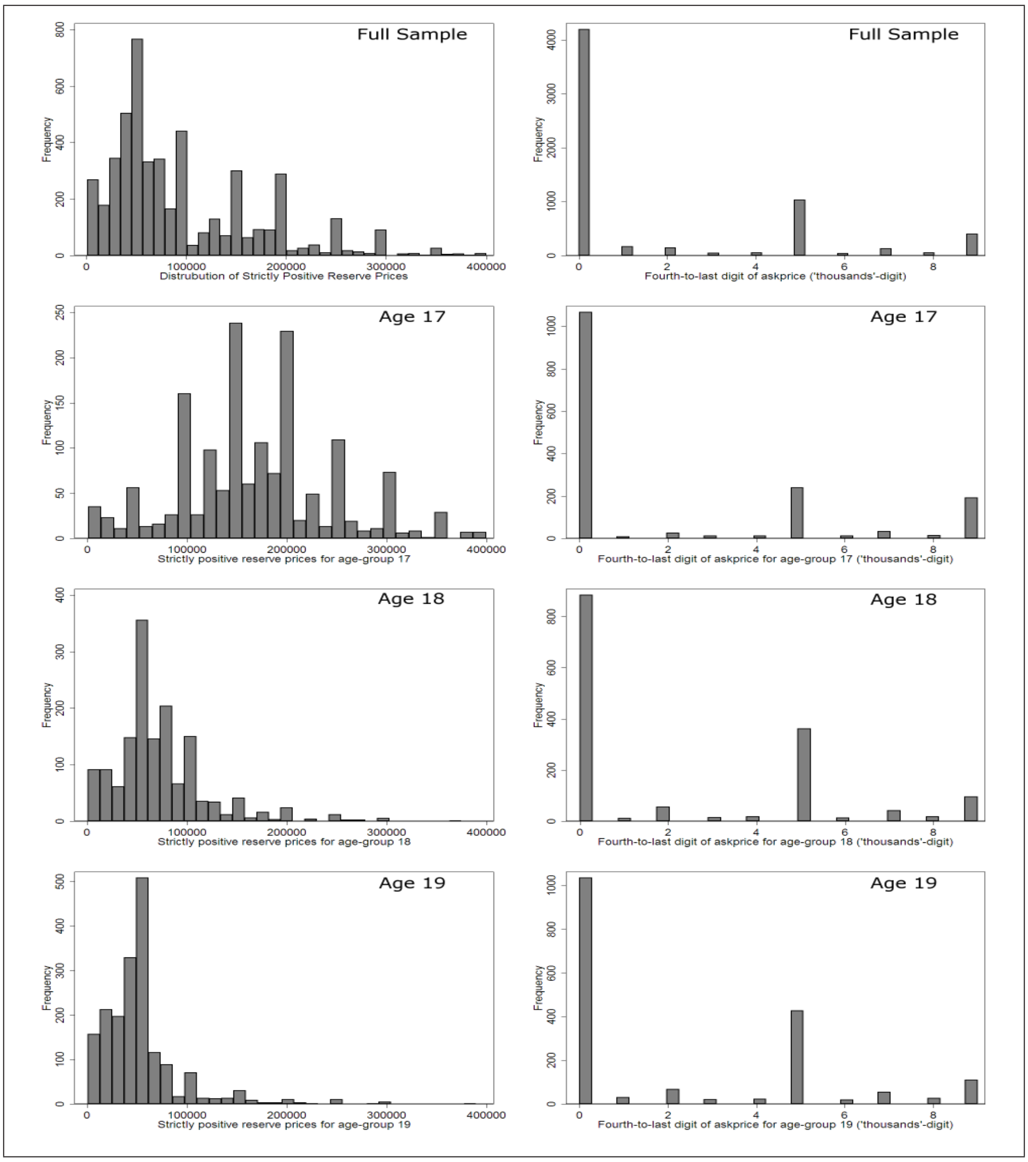
Result 4 (Entitlement effect for acquired players): *Relative to internally promoted players, the average seller in* HT *demands a positive reserve price premium for players they previously acquired on the market* ($\beta_{acquired} > 0$)*. Hypothesis 2 can thus be rejected.*

This finding suggests that the sellers of purchased players fall prey to the *sunk cost fallacy* and *loss aversion*. For instance, a seller might be tempted to regard his own acquisition cost as a benchmark for the reserve price he sets and thus charges at least the same amount, or feels even entitled to demand an additional premium. Yet, this cost is sunk and should rationally not affect his choice. Moreover, since his valuation was the highest in the previous auction, this might be too high a threshold, if a player hasn't significantly increased in quality in the meantime. In contrast, for internally promoted players there is no such benchmark, which would explain the difference in reserve prices that we observe.

Reserve price clustering. While we find final and reserve prices to respond very differently if a player has been traded previously, we already pointed out that the impact of all other influential variables is *qualitatively similar* for both. However, all coefficients for the age variables and also for *tsi* are *quantitatively much larger* in the price regressions than in those for the reserve price. For instance, in column IV of Table 3, holding all other variables constant, a marginal day in age-group seventeen reduces the sales price on average by €1,118, while the analogous effect for the reserve price is only €167, or 15% of the former. Intuitively, the minimum bids react substantially less sensitively to the precise age. A possible explanation for this pattern arises from the fact that the reserve prices are remarkably clustered around focal points at multiples of €50,000, as indicated in Figure 3a above. This intuition is further strengthened by an inspection of the frequency distribution of (non-zero) reserve prices in our sample as depicted in Figure 6.

First, consider the four histograms on the left of Figure 6 which depicts the frequency distribution of (non-zero) reserve prices for the full sample and for each age-group separately. Though they naturally exhibit some variation, we find that reserve prices are *substantially*

Figure 6: Distribution of Reserve Prices and their Fourth-to-last Digits



clustered at multiples of €50,000. The distribution for the full sample exhibits several distinct spikes ranging from €50,000 to €300,000. A similar pattern arises on the individual age-group levels, where the effect is most accentuated for seventeen year old players. In particular, their reserve prices are most frequently set to the (round) values of €100,000, €150,000, and €200,000. The patterns for ages eighteen and nineteen also exhibit strong focal points at €50,000 and at some of its multiples, though less pronounced due to the age-induced decline in the players' values.

Second, we also find evidence for considerable *lower scale clustering*. On the right of Figure 6 we plot the frequency distribution of the fourth-to-last digit (the "thousands"-digit) of the reserve prices. For example, if the reserve price is given by €6**7**,000 the digit takes value

"7". Accordingly, the spikes at the values of 0, 5, and 9 indicate that a majority of reserve prices were set at multiples of €5,000, or just below the next full ten-thousand.

Result 5 (Clustering at round numbers): *The distribution of reserve prices exhibits substantial clusters at multiples of €50,000, and also on a lower scale at multiples of €5,000.*

According to Sonnemans (2006), such (large scale) round number-clustering could be caused by boundedly rational sellers, who form mental target prices, which then serve as a "good enough"-solution in their view instead of considering the precise distribution of bidders' valuations. In line with this intuition, and also with the findings documented in Benartzi and Thaler (2008) for the determination of savings choices, we interpret the strong clustering in the reserve price pattern as evidence for sellers using a round number heuristic, or rule-of-thumb, when making their choice for a reserve price to considerably simplify their decision making.

Moreover, recall that a large fraction of the sellers (18%) sets a reserve price of zero. Both the strong clustering and frequent absence of a positive minimum bid stand in marked contrast to the theoretical predictions for the optimal reserve price in an IPV context. This suggests that many sellers do not efficiently utilize the reserve price as an instrument to maximize their expected revenue. Intuitively, an efficient strategy to appropriate a share of the winning bidder's rent would require a seller to form fine-tuned estimates of the expected (second) highest-order statistic derived from the distribution of valuations rather than to employ a simplifying rule-of-thumb. Moreover, due to the large scale clustering a substantial fraction of reserve prices are set considerably below and above the optimal level. In the latter case, an excessive number of auctions will fail resulting in an inefficient allocation.

4 Optimal Reserve Price and Foregone Revenue

In this section we quantify the economic consequences of suboptimal reserve prices by providing estimates of how much expected revenue is effectively lost as compared to the situation with optimal reserve prices. In doing so, we account for the effect of age on the players' values, and thus on the level of the optimal reserve price, by subdividing our sample into weekly intervals of precise age, yielding a total of 48 "cohorts". Each age-group consists of 16 cohorts, where the intervals are defined such that they only contain players from the same age-group.[35] Abstracting from the small variation of the precise age, we assume that the values for the players within cohort j are realizations from the same underlying value

[35] For example, cohort 16 includes all players in the interval *totalage* $\in [105, 111]$ (i.e. "17 years 105 days" to "17 years 111 days"), while cohort 17 contains those with *totalage* $\in [112, 118]$ (i.e. "18 years 0 days" to "18 years 6 days"). Hence, the birthday effect will take place across but not within the cohorts.

distribution function, $F_j(v)$. Under this assumption, the optimal reserve price, r_j^*, is the same for all players belonging to cohort j.

In the following, we start with a brief description of our approach to determine the optimal reserve price.[36] In particular, we first use the information on the observed sales prices in our data to identify a non-parametric estimate for the valuation primitive of each cohort. By using a Maximum Likelihood method (MLE) to obtain a parametric distribution best describing these point estimates, we then determine the optimal reserve prices and the maximum expected revenues. Subsequently, we present the results from comparing the expected revenues at the actual reserve prices to the corresponding optimal benchmark.

4.1 Estimation of the Optimal Reserve Price

As a first step to estimate the optimal reserve price it proves useful to re-consider the seller's problem in general. In particular, the expected revenue of a seller who sets a reserve price of r for an object for sale is given by

$$\Pi(r) = v_0 F(r)^N + rN(1 - F(r))F(r)^{N-1} + \int_r^{\overline{v}} u(1 - F(u))(N-1)F(r)^{N-2} f(u)du, \qquad (2)$$

where $0 \leq v_0 \leq r$ is the reservation value of the seller and N the number of potential bidders. Under the independent private value (IPV) assumptions, the bidders' individual valuations are i.i.d. draws from the increasing distribution function $F(v)$, the "valuation primitive", which has support $[0, \overline{v}]$ and admits a continuous density function $f(v) \equiv F'(v)$ (see e.g. Krishna, 2002). The first term on the RHS of (2) thus captures the expected utility from the event that none of the N potential buyers realizes a valuation above r and the seller gets v_0, which occurs with probability $F(r)^N$. The second term reflects the event where all but one bidder have a lower valuation than r, which occurs with probability $N(1 - F_j(r))F_j(r)^{N-1}$. In that case, the winning bid equals r and the seller successfully manages to reap some of the winner's surplus. Finally, the third term states the expected sales price conditional on more than one bidder having a valuation of at least r. The choice for the reserve price thus involves a trade off between a higher probability that the auction fails and realizing additional gains from a sales price above the second-highest bidder's valuation.

[36] For the sake of brevity, we omit the details of the calculus, which was performed with Matlab and follows the algorithm laid out in Paarsch & Hong (2006). The corresponding m-files can be requested from the authors. All proofs for the validity of the applied approach are available in standard textbooks, e.g. Paarsch & Hong (2006) and Krishna (2002).

As a general result under IPV, for any arbitrary value distribution function $F(v)$, the optimal reserve price r^* that maximizes (2) is independent of the number of potential bidders and given by

$$r^* = v_0 + \frac{1}{\mu(r^*)}, \tag{3}$$

where $\mu(v) \equiv \frac{1-F(v)}{f(v)}$ is the hazard rate of $F(v)$ (see Riley & Samuleson, 1981). Thus, the optimal reserve price r^* will always lie above v_0 and depends on the valuation primitive of the bidders, which is unknown the econometrician.

However, $F(v)$ is non-parametrically identified from the winning bids, i.e. the observed sales prices (Athey & Haile, 2002). Depending on the auction format, the latter describe the empirical distribution of the i^{th} order statistic from an i.i.d. sample of size N from the valuation primitive $F(v)$. Since the auction format in *HT* is strategically equivalent to a sealed-bid-second-price auction, the winning bid equals the second-highest bid plus one discrete increment, whenever the reserve price was set below the second highest bidder's valuation.[37]

Denote by w_{jk} the observed sales price of auction $k = 1, ..., K_j$ in cohort j. Hence, the K_j sales prices observed for cohort j describe an empirical distribution function $\hat{F}_j(w_{jk})$,[38] which is equivalent to the distribution of the second-highest order statistic of the valuation primitive, i.e. the distribution of the second-highest valuations $F_{(2)j}(v, N_{jk})$:

$$\hat{F}_j(w_{jk}) \equiv F_{(2)j}(v; N_{jk}) = N_{jk} \cdot F_j(v)^{N_{jk}-1} - (N_{jk} - 1) \cdot F_j(v)^{N_{jk}}, \tag{4}$$

where N_{jk} is the number of potential bidders in auction k in cohort j. Though the reserve price is independent of N_{jk}, it enters the distribution of the second-highest order statistic, which in the following is used to identify the valuation primitive $F_j(v)$. However, we have no information on how many potential bidders will view a particular player. At this point, we therefore need to make a simplifying assumption on the value of N_{jk} used to obtain the estimate of $F_j(v)$.

Assumption 1 (Potential number of bidders): *The number of potential bidders is exogenously fixed and identical for all auctions in the sample:* $N_{jk} = N \; \forall \; j, k$.

In addition, we borrow on the dataset of 17,510 *HT*-auctions from the study of the demand side in Englmaier & Schmöller (2009) to determine appropriate values for N to be used in the estimation. Conveniently, their data contain information on the number of bids placed

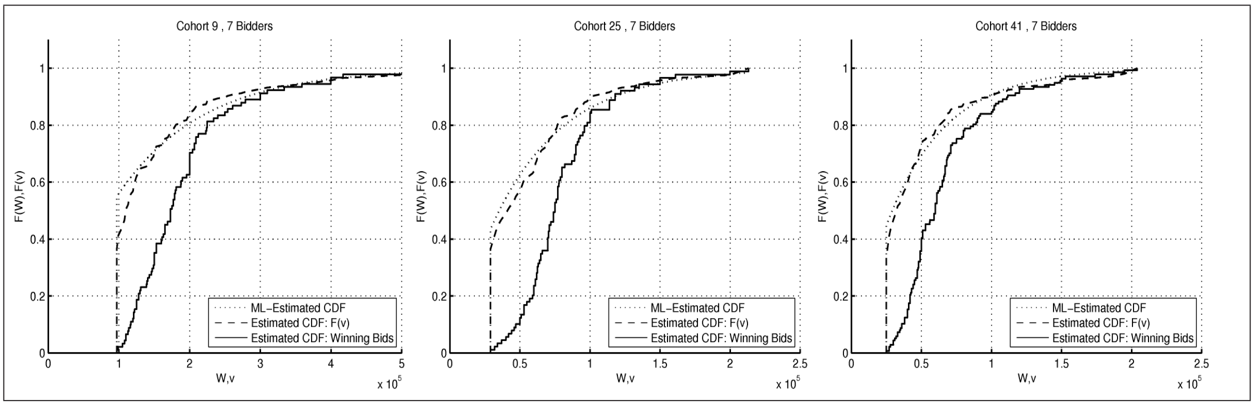
[37] In a sealed-bid second price auction, the equilibrium bidding strategy is to place a bid equal to one's own valuation, v_i, while in the English ascending open bid auction a bidder will repeatedly increase his bid until the current price reaches v_i and exit thereafter.

[38] Given a vector of length T, an empirical distribution function is a cumulative probability distribution function that concentrates a probability of $1/T$ at each of the T elements in the vector.

in each auction.[39] We argue that this is a reasonable proxy for the potential number of bidders viewing an individual player on the transfer market. In particular, we obtain the point estimates of $F_j(v)$ for $N = 7$, which is equal to the median number of bids in these data.[40]

By substituting $N = 7$ and the values for $\hat{F}_j(w_{jk})$ into (4), we are able to obtain point estimates of the valuation primitive for each of the 48 cohorts by numerically solving for the roots with respect to $F_j(v)$. As the results are qualitatively similar for all j, Figure 7 shows the results from this approach for a representative cohort in the middle of each age-group.

Figure 7: Distribution Functions of First- and Second-Highest Order Statistic and ML-Estimator



The figure depicts the empirical distribution $\hat{F}_j(w_{jk})$ of the winning bids and the corresponding point estimates of the valuation primitive $F_j(v)$ for cohorts $j = \{9, 25, 41\}$. For every j, $\hat{F}_j(w_{jk})$ resembles the cumulative distribution function (CDF) of a normal distribution, and $F_j(v)$ is approximately exponentially distributed. Assuming the valuation primitive indeed follows an exponential distribution, we have that

$$F_j(v) \xrightarrow{\text{MLE}} \tilde{F}_j(v; \lambda_j) = 1 - e^{-\lambda_j v} \quad \forall \;\; v \in \mathbb{R}_0^+ \tag{5}$$

where λ_j is the Maximum-Likelihood estimator (MLE) for the rate parameter of the exponential distribution $\tilde{F}_j(v; \lambda_j)$ best describing $F_j(v)$, which is also depicted in Figure 7.[41]

Having derived an estimator for the underlying valuation primitive $F_j(v)$ for the players in cohort j, we are able to determine the corresponding optimal reserve price r_j^* up to a constant, i.e. the reservation value v_0 of the seller. However, v_0 is not observed and thus

[39]For a graphical illustration of the distribution of the number of bids see Figure 12 in Appendix 6.

[40]To account for the effect of the number of potential bidders we repeated the estimation for $N = 13$ (mean number of bids), $N = 2$ (25th-percentile), and $N = 18$ (75th-percentile). For a discussion of the results see Section 4.2 below. All tables are available from the authors upon request.

[41]Given the exponential formulation and k observations in cohort j, the log-likelihood function used to estimate λ_j depends on the density of the second-highest-order statistic, $\tilde{f}_{(2)j}(v, \lambda_j)$, and is given by $\ell(\lambda_j) = \sum\limits_k ln(\tilde{f}_{(2)j}(v, \lambda_j)) = \sum\limits_k \left[ln\big(N(N-1)\big) + ln\big(1 - \tilde{F}_j(v, \lambda_j)\big) + (N-2)ln\big(\tilde{F}_j(v, \lambda_j)\big) + ln\big(\tilde{f}_j(v, \lambda_j)\big)\right]$.

unknown. Therefore, the estimation results for the optimal reserve prices additionally rely on the following simplifying assumption.

Assumption 2 (Reservation Values): *The reservation value v_0 is constant across all sellers and given by the consumption value (CV) of the players in the sample.*

In particular, the fact that a player is offered for sale implicitly signals that his current owner does not consider him as a suitable trainee for his current training-strategy. Given this rationale, our belief is that it is plausible to assume that the value he attaches to the player is likely to reflect the latter's CV. As a proxy for the CV of the players in our sample, we take about 80% of the average sales price (€ 48,921) observed for the oldest players, i.e. cohort 48, yielding an assumed value of $v_0 = 40,000$ for the reservation value of the sellers.[42]

Table 5 shows the resulting estimates of the optimal reserve price for each cohort, which are obtained by substituting v_0 and $\tilde{F}_j(v; \lambda_j)$ into (3). In addition, we state the number of observed winning bids, on which the identification of $\tilde{F}_j(v; \lambda_j)$ is based. Except for cohorts $j = 1$ and $j = 2$, the youngest players in the sample, all estimates are based on more than 70 observations, yielding reasonably precise descriptions of the underlying valuation primitives.

Table 5: Optimal and Actual Reserve Prices by Cohort

Age 17					Age 18					Age 19				
j	K_j	r_j^*	r_j^{med}	r_j^{mean}	j	K_j	r_j^*	r_j^{med}	r_j^{mean}	j	K_j	r_j^*	r_j^{med}	r_j^{mean}
1	23	241,112	150,000	135,000	17	73	109,036	61,250	68,395	33	124	82,590	40,000	45,727
2	26	229,899	150,000	151,845	18	92	96,575	55,000	66,860	34	131	80,877	40,000	39,464
3	73	198,265	150,000	154,250	19	84	96,970	60,000	60,121	35	122	77,021	35,000	39,257
4	102	189,391	150,000	150,026	20	99	92,687	50,000	50,188	36	119	80,142	39,500	38,888
5	90	178,115	150,000	146,889	21	93	96,593	50,000	50,333	37	105	77,077	35,000	38,167
6	76	177,689	150,000	152,053	22	91	92,133	50,000	60,841	38	100	78,665	35,000	36,332
7	102	171,840	150,000	138,127	23	102	91,521	50,000	52,082	39	112	81,601	39,000	34,705
8	108	165,431	150,000	141,765	24	109	101,381	50,000	62,222	40	110	79,073	37,500	37,782
9	91	161,678	150,000	145,988	25	89	90,902	50,000	52,565	41	137	82,155	39,001	39,956
10	105	158,699	150,000	145,404	26	95	93,371	50,000	55,163	42	120	78,161	35,000	43,281
11	80	152,832	150,000	145,500	27	77	88,999	50,000	54,450	43	113	79,655	40,000	38,767
12	87	153,830	175,000	162,195	28	73	88,684	50,000	53,206	44	132	76,097	37,500	39,126
13	87	148,599	150,000	159,118	29	83	91,992	52,500	58,544	45	146	78,623	35,000	41,171
14	84	151,867	150,000	157,731	30	105	88,497	50,000	47,912	46	139	78,166	35,000	34,869
15	87	147,818	150,000	145,702	31	106	88,257	50,000	56,641	47	109	76,930	40,000	37,731
16	87	133,922	139,001	130,970	32	101	85,944	49,000	50,404	48	137	78,602	35,000	37,961

As we would expect, an inspection of the stated values for r_j^* shows a clear tendency of the level of the optimal reserve price to decline as age increases. Note that the estimates

[42] While the age-dependent APV will be very small for players at the end of age-group nineteen, Englmaier & Schmöller (2009) still find evidence for a small birthday effect at the age of twenty. Therefore, we adjust our estimate of the CV downward to the value of € 40,000. All results remain robust, if we instead employ the average sales price of the oldest players in age-group nineteen as a proxy for v_0.

for $F_j(v)$, from which the respective values for r_j^* are calculated, are solely based on the observed sales prices in cohort j, which may be subject to considerable variation. Considering this fact, it is not surprising that the decline is not strictly monotonic across all cohorts. Importantly, however, observe that the estimated optimal reserve price exceeds the median (r_j^{med}) and mean (r_j^{mean}) of the observed minimum bids for almost all cohorts, and often quite substantially.

4.2 Expected Revenue at Optimal and Actual Reserve Prices

In Section 3 we have shown that a substantial fraction of sellers sets either no reserve price or uses a round-number heuristic to simplify their decision making. For example, note that 22 (17%) of the 130 sellers in cohort $j = 9$ set a reserve price of zero, 17 (13%) opted for a value of €150,000, 11 (8%) chose €200,000, and the values of €100,000 and €250,000 were each observed in 6 (5%) auctions, all together accounting for about half of the sellers. The patterns for the other cohorts are quite similar. Therefore, we are particularly interested how the expected revenues for these sellers compare to the estimated optimum.

Given the approximated valuation primitive $\tilde{F}_j(v; \lambda_j)$, analogously to (2) the expected revenue at a reserve price of r_j for a player from cohort j is given by

$$\tilde{\Pi}(r_j) = v_0 \tilde{F}_j(r)^N + rN(1 - \tilde{F}_j(r))\tilde{F}_j(r)^{N-1} + \int_{r_j}^{\overline{v}} u(1 - \tilde{F}_j(u))(N-1)\tilde{F}_j(u)^{N-2}\tilde{f}_j(u)du, \quad (6)$$

where we denote $\tilde{F}_j(v) \equiv \tilde{F}_j(v; \lambda_j)$ to simplify the notation. For the values of N and v_0 assumed above, the maximum expected revenue for each cohort is given by substituting r_j^* into (6), where we additionally employ the 99th-percentile of the observed sales price in each cohort as a proxy for $\overline{v}$. Similarly, we are able to determine the expected revenue for any reserve price observed in our sample. By comparing the resulting outcomes to the respective optimum, we are thus able to determine the shares of expected revenue lost due to deviations from the optimal reserve price.

Table 6 states results for age-group seventeen at several preeminent points of the actual reserve price pattern, including zero and the main cluster points as indicated in Figure 6.[43] To simplify the notation, we refer to a cluster point by C_x, where x indicates its respective magnitude.

At a first glance, the deviations from the optimum appear to be small. The expected revenues at the mean and median of the actual reserve prices (columns II and III) are remarkably close

[43]The corresponding results for age-groups eighteen and nineteen are qualitatively similar as shown in Tables 9 and 10 in Appendix 6.

Table 6: Expected Revenues for Age-Group 17 (Cohorts 1-16)

		I	II	III	IV	V	VI	VII	VIII
Coh.	Obs.	$\tilde{\Pi}(r_j^*)$	$\tilde{\Pi}(r_j^{mean})$	$\tilde{\Pi}(r_j^{med})$	$\tilde{\Pi}(0)$	$\tilde{\Pi}(C_{50})$	$\tilde{\Pi}(C_{100})$	$\tilde{\Pi}(C_{200})$	$\tilde{\Pi}(C_{250})$
1	24	263,433	260,425	260,858	259,570	259,575	259,791	262,635	263,383
			(-1.1%)	(-1.0%)	(-1.5%)	(-1.5%)	(-1.4%)	(-0.3%)	(-0.0%)
2	29	264,041	261,800	261,734	260,208	260,215	260,488	263,552	263,747
			(-0.8%)	(-0.9%)	(-1.5%)	(-1.4%)	(-1.3%)	(-0.2%)	(-0.1%)
3	89	236,296	235,121	234,937	232,506	232,523	233,071	236,293	233,470
			(-0.5%)	(-0.6%)	(-1.6%)	(-1.6%)	(-1.4%)	(-0.0%)	(-1.2%)
4	127	225,672	224,625	224,623	221,878	221,900	222,573	225,563	221,372
			(-0.5%)	(-0.5%)	(-1.7%)	(-1.7%)	(-1.4%)	(-0.0%)	(-1.9%)
5	104	213,323	212,543	212,673	209,507	209,539	210,419	212,779	206,451
			(-0.4%)	(-0.3%)	(-1.8%)	(-1.8%)	(-1.4%)	(-0.3%)	(-3.2%)
6	97	197,134	196,581	196,499	193,318	193,350	194,239	196,565	190,148
			(-0.3%)	(-0.3%)	(-1.9%)	(-1.9%)	(-1.5%)	(-0.3%)	(-3.5%)
7	131	207,082	206,140	206,643	203,246	203,286	204,309	206,095	198,386
			(-0.5%)	(-0.2%)	(-1.9%)	(-1.8%)	(-1.3%)	(-0.5%)	(-4.2%)
8	139	194,449	193,908	194,203	190,583	190,634	191,829	192,816	183,568
			(-0.3%)	(-0.1%)	(-2.0%)	(-2.0%)	(-1.3%)	(-0.8%)	(-5.6%)
9	130	195,223	194,958	195,072	191,336	191,394	192,704	193,105	182,905
			(-0.1%)	(-0.1%)	(-2.0%)	(-2.0%)	(-1.3%)	(-1.1%)	(-6.3%)
10	142	186,261	186,061	186,173	182,354	182,420	183,828	183,696	172,719
			(-0.1%)	(-0.0%)	(-2.1%)	(-2.1%)	(-1.3%)	(-1.4%)	(-7.3%)
11	134	172,300	172,232	172,290	168,347	168,430	170,054	168,669	156,131
			(-0.0%)	(-0.0%)	(-2.3%)	(-2.2%)	(-1.3%)	(-2.1%)	(-9.4%)
12	155	181,025	180,928	180,363	177,081	177,160	178,746	177,593	165,323
			(-0.1%)	(-0.4%)	(-2.2%)	(-2.1%)	(-1.3%)	(-1.9%)	(-8.7%)
13	164	170,543	170,377	170,540	166,549	166,648	168,448	165,977	152,311
			(-0.1%)	(-0.0%)	(-2.3%)	(-2.3%)	(-1.2%)	(-2.7%)	(-10.%)
14	147	177,945	177,897	177,940	173,983	174,069	175,732	174,113	161,318
			(-0.0%)	(-0.0%)	(-2.2%)	(-2.2%)	(-1.2%)	(-2.2%)	(-9.3%)
15	140	172,311	172,304	172,304	168,308	168,410	170,245	167,555	153,684
			(-0.0%)	(-0.0%)	(-2.3%)	(-2.3%)	(-1.2%)	(-2.8%)	(-10.%)
16	131	149,788	149,774	149,743	145,594	145,781	148,326	140,746	123,583
			(-0.0%)	(-0.0%)	(-2.8%)	(-2.7%)	(-1.0%)	(-6.0%)	(-17.%)

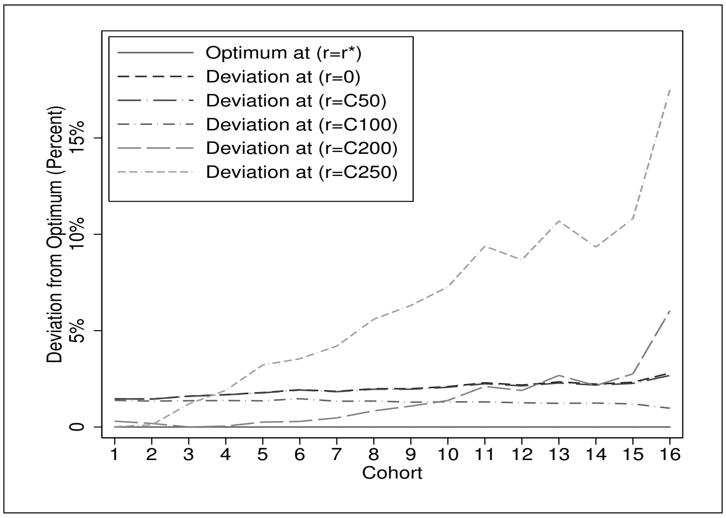
Notes: Deviations from the maximum expected revenue are stated in parentheses. Since largely identical to the respective median reserve price (see Table 5), the results for cluster point C_{150} are omitted from the presentation.

to $\tilde{\Pi}(r_j^*)$. If we consider the sellers who abstain from setting a positive reserve price (column IV), we find that they only lose a share of about 2% relative to the optimum. Moreover, also the deviations at the cluster points C_{50} and C_{100} (columns V and VI) are of similar magnitude. Returning to Table 5, note that all of these values are located considerably below r_j^* for $j \in \{1, ..., 16\}$. As a consequence, at these levels the reserve price is likely to be non-binding in the sense that the odds for at least two of the assumed $N = 7$ potential bidders realizing a higher valuation are reasonably large. Intuitively, these sellers forego the chance to gain additional rents from setting a reserve price that lies above the expected second-highest bidder's valuation. The auction outcome is thus effectively determined by the degree of competition among the potential bidders.

A higher number of potential bidders implies a larger number of i.i.d. draws from the valuation primitive. Since this ceteris paribus increases the probability for the realization of high valuations, competition is more intense for higher N. Consistently, in the estimation for $N = 13$ and $N = 18$ the shares of expected revenue lost relative to the optimum are of even smaller magnitude than for $N = 7$. Conversely, for $N = 2$ potential bidders also the expected revenues at zero, C_{50}, and C_{100} dramatically deviate from the optimum, since the compensating impact of bidder competition is substantially reduced. Since HT's transfer market is highly competitive, our intuition is that the assumption of at least $N = 7$ potential bidders is indeed justified and that the finding of a relatively small loss in expected revenue due to a suboptimally low reserve price adequately describes the actual situation.

As soon as the minimum bid exceeds the optimal reserve price, however, the shares of foregone expected revenue increase substantially. Intuitively, an exaggerated minimum bid induces an inefficiently high probability that the auction fails, which causes the expected revenues for the seller to decline. For instance, the optimal reserve price in cohort $j = 9$ is given by $r_9^* = 161,678$. Yet, 15% of the sellers charged an reserve price equal to or above C_{250}, thereby accruing a loss of more than 6.3% relative to the optimum. Moreover, the more the chosen minimum bid exceeds r_j^*, the larger is the share of expected revenue lost. In cohort $j = 16$, in 10% of the 131 auctions the seller demanded a starting price of C_{250} or higher, thereby reducing his expected revenue by more than 17% relative to the optimum. Figure 8 illustrates the respective deviations for all 16 cohorts in age-group seventeen.[44] Clearly, the shares of expected revenue lost at minimum bids at levels of C_{200} and C_{250} are amplified for older players in the age-group, since the respective optimal reserve prices decline as age increases and thus are exceedingly outvalued. Consistent with the above argument that bidder competition triggers a compensating effect, for reserve prices below r_j^*, i.e. $r_j \in \{0, C_{50}, C_{100}\}$, the measured deviations remain relatively constant.

Figure 8: Share of Expected Revenue Lost (Age-Group 17)



[44]For an analogous illustration for age-groups eighteen and nineteen see Figure 13 in Appendix 6.

Result 6 (Loss of expected revenue): *The impact of a suboptimal reserve price depends on the direction of the deviation from its optimal level. Downward deviations, i.e. setting a non-binding reserve price, are largely countervailed by the fact that competition among the potential bidders is sufficiently intense. In contrast, upward deviations can cause substantial reductions in expected revenue.*

Summarizing, though suboptimal from a theoretical perspective, the large number of zero reserve prices and cluster points we observe in our data not necessarily trigger severe losses in revenue. As long as the reserve price is set below its optimal level, the competitive environment of the transfer market suffices to guarantee an almost optimal expected revenue for the seller, though he will not succeed to additionally extract some of the winning bidder's surplus. In contrast, a large fraction of sellers loses a substantial share of expected revenue by setting a reserve price too high, thereby increasing the probability that the player remains unsold.

5 Conclusion

We examine empirically how managers playing the online game HATTRICK set reserve prices in auctions for virtual players. Using detailed field data on 6,258 auctions from *HT*'s transfer market, we find that chosen reserve prices exhibit both, very sophisticated and suboptimal behavior by the sellers. Reserve prices pick up the birthday effect of the demand side documented in Englmaier & Schmöller (2009) and are adjusted remarkably nuanced to the resulting sales price pattern. All our results are robust if we additionally control for the experience of sellers, the auction-end-day, and time-of-day effects.

Intriguingly, even though *HT*'s transfer market is highly competitive, we find evidence consistent with a sunk cost fallacy and a resulting entitlement effect in form of a large positive premium on the reserve price when a player has been previously acquired.

While many sellers act strategically and try to reap some of the buyers' surplus, some fail in this endeavor as they set reserve prices suboptimally. We have established that reserve prices are too clustered (around € 50,000 steps) to be consistent with fully rational behavior and we document what share of expected revenues is foregone by this. We thus conjecture that many *HT* managers simplify their decision making by adopting heuristic pricing rules that are suboptimal from a fully rational point of view.

If, as in our data, the entitlement and clustering effects are persistent and quantitatively relevant, the option of choosing a reserve price might be an impediment to market efficiency as sellers set too high reserve prices resulting in too little trade. In such situations a social planner might want to avoid using a reserve price in the design of an auction format to prevent this potential distortion.

On the upside, our findings suggest that simple microeconomic theory gives us a lot of mileage in explaining market behavior in complex environments. We document that (the majority of) sellers very finely adjust their behavior to demand patterns and try to strategically exploit potential arbitrage possibilities. Moreover, we are able to show that the adoption of heuristic pricing rules by the sellers does not affect the expected revenue from an auction dramatically, as long as the chosen reserve price lies below the optimal level and competition among the bidders is sufficiently intense.

Clearly, more research on the behavior of sellers under different auction formats is needed to improve our understanding of the determinants and effects of reserve prices and to evaluate the efficiency of different market designs. Much of the existing evidence derives from field data or field experiments. Hence, it might be worthwhile to conduct controlled laboratory experiments with focus on the supply side of auction markets. They allow for a systematic variation of the design features that might possibly drive the behavioral patterns observed in the field, while at the same time resolving many factors of uncertainty like the lack of knowledge of the underlying valuation primitive. Alternatively, as a way of bridging the gap between the lab and the field, virtual economies like *HT* may also serve as platforms to conduct controlled economic and social experiments. Although considerably more complex than most laboratory experiments, and despite the missing monetary incentives, the findings presented in this and other studies (see e.g. Trautmann & Traxler, 2009, Castronova, 2008, and Nicklisch & Salz, 2008) suggest that they provide a market framework which adheres to standard economic constraints while still providing a considerable degree of control.

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6 Appendix

Table 7: Denomination of Skill Levels

Skill Label	Integer Score	Skill Label	Integer Score
non-existent	0	brilliant	11
disastrous	1	magnificent	12
wretched	2	world class	13
poor	3	supernatural	14
weak	4	titanic	15
inadequate	5	extra-terrestrial	16
passable	6	mythical	17
solid	7	magical	18
excellent	8	utopian	19
formidable	9	divine	20
outstanding	10		

Table 8: Determinants of Price Unconditional on Sale (Tobit)

Dep.Var.: *price*	Coeff.	Std. Dev
days17	-1609.81***	64.72
days18	-138.30**	56.70
days19	-10.70	49.68
age18	-173269.62***	5834.23
age19	-196106.93***	5644.17
tsi	88.22***	4.75
acquired	-13578.76***	3203.95
Intercept	79122.68***	16476.41
skills	yes	
character	yes	
daytime	yes	
weekday	yes	
LR Chi(28)	2587.09	
N (1515 left-cens. at 0)	6258	

Notes: The TOBIT procedure also includes failed auctions with a sales price of zero (left-censored). Standard errors are stated in parentheses. Asterisks denote statistical significance at the 1%(***), 5%(**) or 10%(*) level.

Table 9: Expected Revenues for Age-Group 18 (Cohorts 17-32)

		I	II	III	IV	V	VI	VII
Coh.	Obs.	$\tilde{\Pi}(r_j^*)$	$\tilde{\Pi}(r_j^{mean})$	$\tilde{\Pi}(r_j^{med})$	$\tilde{\Pi}(0)$	$\tilde{\Pi}(C_{50})$	$\tilde{\Pi}(C_{100})$	$\tilde{\Pi}(C_{150})$
17	102	113,912	111,070	110,433	109,007	109,656	113,710	109,149
			(-2.5%)	(-3.1%)	(-4.3%)	(-3.7%)	(-0.2%)	(-4.2%)
18	125	94,990	92,663	91,217	89,365	90,691	94,950	85,867
			(-2.5%)	(-4.0%)	(-5.9%)	(-4.5%)	(-0.0%)	(-9.6%)
19	111	94,375	91,187	91,173	88,780	90,075	94,344	85,405
			(-3.4%)	(-3.4%)	(-5.9%)	(-4.6%)	(-0.0%)	(-9.5%)
20	116	88,289	84,047	84,025	82,346	84,025	88,089	77,669
			(-4.8%)	(-4.8%)	(-6.7%)	(-4.8%)	(-0.2%)	(-12.%)
21	119	94,140	89,874	89,841	88,517	89,841	94,101	85,025
			(-4.5%)	(-4.6%)	(-6.0%)	(-4.6%)	(-0.0%)	(-9.7%)
22	123	87,899	85,079	83,643	81,905	83,643	87,664	77,068
			(-3.2%)	(-4.8%)	(-6.8%)	(-4.8%)	(-0.3%)	(-12.%)
23	125	86,968	82,985	82,722	80,918	82,722	86,692	75,909
			(-4.6%)	(-4.9%)	(-7.0%)	(-4.9%)	(-0.3%)	(-12.%)
24	141	99,835	96,692	95,533	94,534	95,533	99,830	92,529
			(-3.1%)	(-4.3%)	(-5.3%)	(-4.3%)	(-0.0%)	(-7.3%)
25	115	85,880	81,979	81,645	79,771	81,645	85,559	74,592
			(-4.5%)	(-4.9%)	(-7.1%)	(-4.9%)	(-0.4%)	(-13.%)
26	117	89,884	86,234	85,611	84,001	85,611	89,722	79,524
			(-4.1%)	(-4.8%)	(-6.5%)	(-4.8%)	(-0.2%)	(-11.%)
27	104	81,142	77,587	76,950	74,838	76,950	80,653	69,175
			(-4.4%)	(-5.2%)	(-7.8%)	(-5.2%)	(-0.6%)	(-14.%)
28	105	82,464	78,741	78,280	76,126	78,280	81,944	70,390
			(-4.5%)	(-5.1%)	(-7.7%)	(-5.1%)	(-0.6%)	(-14.%)
29	124	86,198	83,066	82,254	80,191	81,944	85,954	75,314
			(-3.6%)	(-4.6%)	(-7.0%)	(-4.9%)	(-0.3%)	(-12.%)
30	136	81,068	76,603	76,890	74,710	76,890	80,529	68,930
			(-5.5%)	(-5.2%)	(-7.8%)	(-5.2%)	(-0.7%)	(-15.%)
31	139	82,104	78,925	77,932	75,719	77,932	81,539	69,886
			(-3.9%)	(-5.1%)	(-7.8%)	(-5.1%)	(-0.7%)	(-14.%)
32	131	74,430	70,400	70,180	67,772	70,336	73,587	61,488
			(-5.4%)	(-5.7%)	(-8.9%)	(-5.5%)	(-1.1%)	(-17.%)

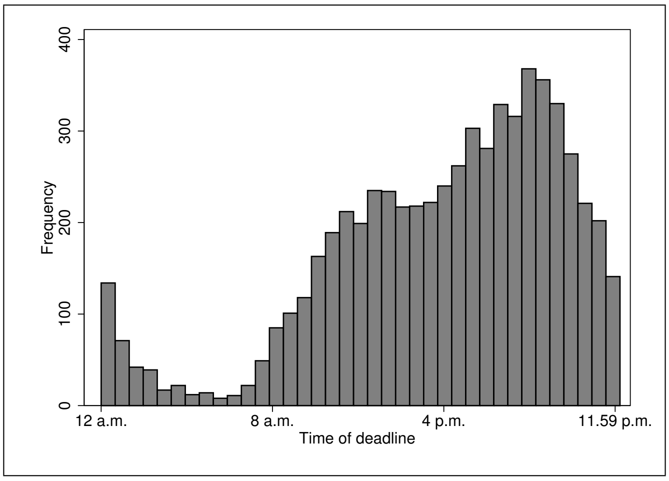
Notes: Deviations from the maximum expected revenue are stated in parentheses.

Table 10: Expected Revenues for Age-Group 19 (Cohorts 33-48)

		I	II	III	IV	V	VI
Coh.	Obs.	$\tilde{\Pi}(r_j^*)$	$\tilde{\Pi}(r_j^{mean})$	$\tilde{\Pi}(r_j^{med})$	$\tilde{\Pi}(0)$	$\tilde{\Pi}(C_{50})$	$\tilde{\Pi}(C_{100})$
33	160	73,387	68,706	67,818	66,271	69,454	72,032
			(-6.4%)	(-7.6%)	(-9.7%)	(-5.4%)	(-1.8%)
34	165	72,115	66,423	66,506	64,729	68,289	70,451
			(-7.9%)	(-7.8%)	(-10.%)	(-5.3%)	(-2.3%)
35	151	64,982	59,187	58,430	56,885	61,477	62,535
			(-8.9%)	(-10.%)	(-12.%)	(-5.4%)	(-3.8%)
36	144	69,869	64,070	64,167	62,360	66,096	68,065
			(-8.3%)	(-8.2%)	(-10.%)	(-5.4%)	(-2.6%)
37	127	64,422	58,422	57,873	56,337	60,911	61,987
			(-9.3%)	(-10.%)	(-12.%)	(-5.4%)	(-3.8%)
38	118	68,667	62,415	62,218	60,893	65,011	66,566
			(-9.1%)	(-9.4%)	(-11.%)	(-5.3%)	(-3.1%)
39	138	71,575	65,288	65,836	64,306	67,702	70,045
			(-8.8%)	(-8.0%)	(-10.%)	(-5.4%)	(-2.1%)
40	139	68,075	62,068	62,023	60,377	64,386	66,058
			(-8.8%)	(-8.9%)	(-11.%)	(-5.4%)	(-3.0%)
41	175	73,928	68,342	68,208	66,746	70,021	72,498
			(-7.6%)	(-7.7%)	(-9.7%)	(-5.3%)	(-1.9%)
42	152	66,852	61,839	60,371	58,983	63,240	64,647
			(-7.5%)	(-9.7%)	(-11.%)	(-5.4%)	(-3.3%)
43	138	70,707	64,875	65,077	63,113	66,971	68,806
			(-8.2%)	(-8.0%)	(-10.%)	(-5.3%)	(-2.7%)
44	165	64,965	59,139	58,816	56,673	61,554	62,321
			(-9.0%)	(-9.5%)	(-12.%)	(-5.3%)	(-4.1%)
45	186	68,156	62,728	61,705	60,374	64,504	66,046
			(-8.0%)	(-9.5%)	(-11.%)	(-5.4%)	(-3.1%)
46	169	64,349	57,849	57,868	56,480	60,736	62,144
			(-10.%)	(-10.%)	(-12.%)	(-5.6%)	(-3.4%)
47	137	63,836	57,752	58,187	55,721	60,340	61,370
			(-9.5%)	(-8.9%)	(-12.%)	(-5.5%)	(-3.9%)
48	171	68,474	62,479	62,021	60,688	64,823	66,360
			(-8.8%)	(-9.4%)	(-11.%)	(-5.3%)	(-3.1%)

Notes: Deviations from the maximum expected revenue are stated in parentheses.

Figure 9: Distribution of Auction End-Times



Notes: During a typical day, the time of the auction deadlines is approximately similarly distributed as the number of simultaneously logged-on users. During the early morning hours CET we observe the lowest traffic with roughly 7,000 online users at its minimum, while during the peak-periods between 5:30 p.m. and 10 p.m. levels up to 75,000 simultaneously online users are reached.

Figure 10: Transfer Market - Search Mask

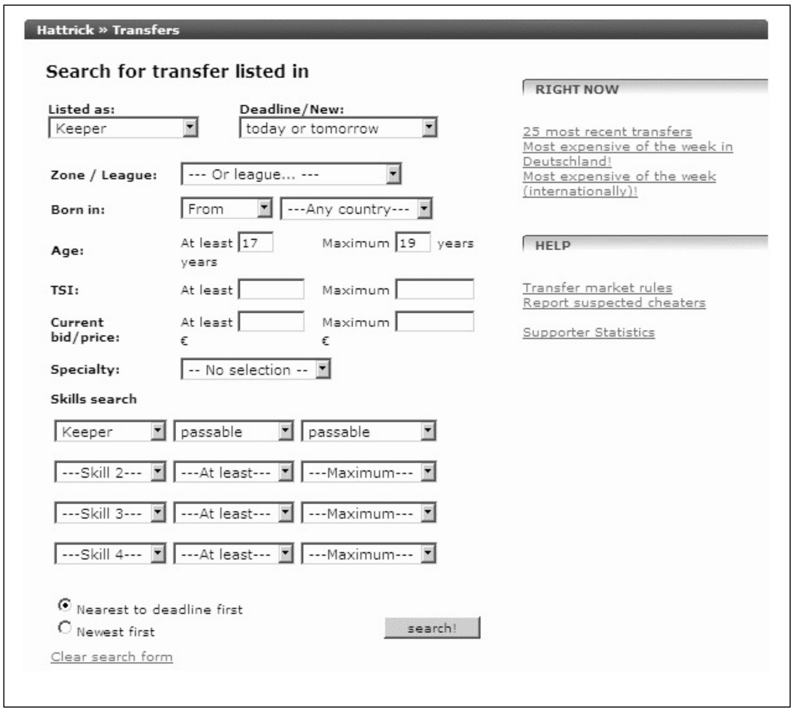


Figure 11: Transfer Market - Search Results Overview

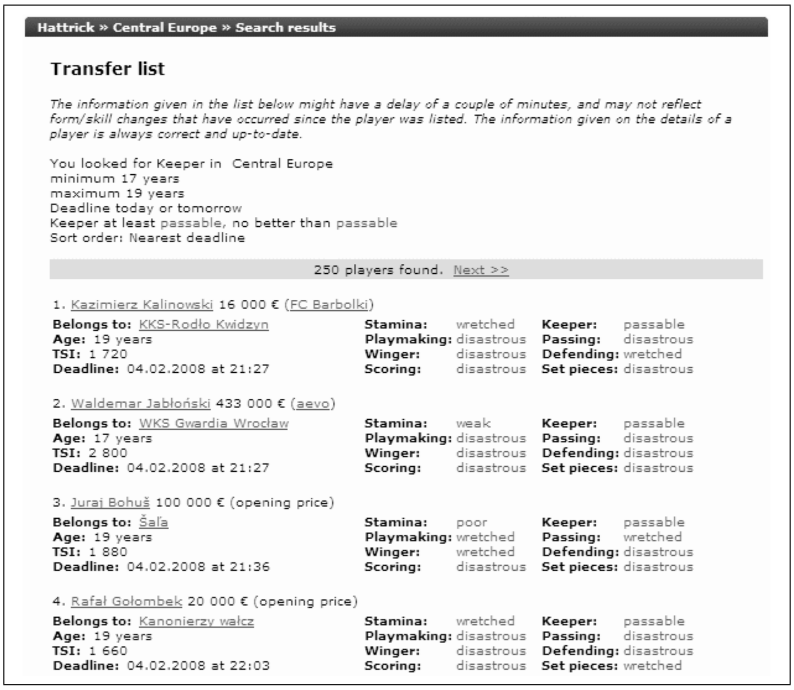
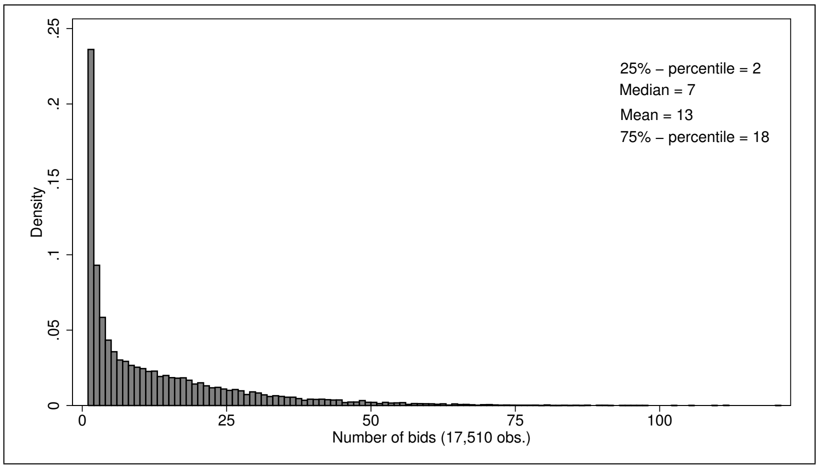
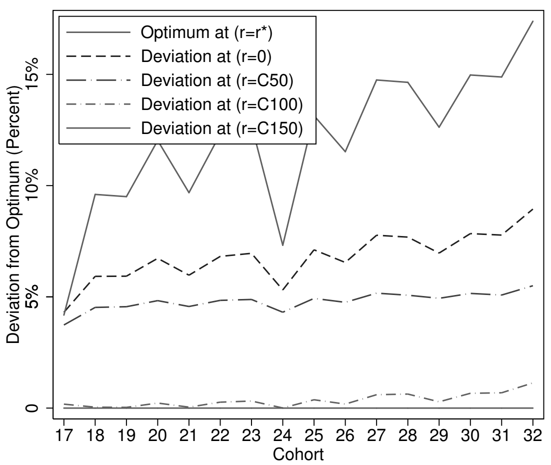


Figure 12: Distribution of the Number of Bids

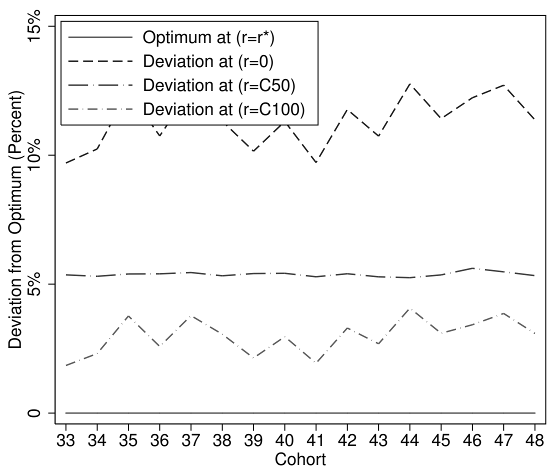


Notes: The graph depicts the distribution of the number of bids observed in the sample of 17,510 HATTRICK-auctions that was analyzed in Englmaier & Schmöller (2009). We employ this information as a proxy for the number of bidders in the estimation of the valuation primitive.

Figure 13: Share of Expected Revenue Lost for Age-Groups 18 and 19



(a) Age-Group 18



(b) Age-Group 19