JDDM
JOURNAL OF DYNAMIC DECISION MAKING

Open Access

Original Research

Anchoring and traffic effects in the virtual market platform of FIFA 20

Andrei Popescu and Klaus Fiedler

Department of Psychology, Heidelberg University, Heidelberg, Germany

An Internet-based competitive marketing game, FIFA 20, served to investigate the effectiveness of two opposite strategies in soccer-player auctions under seminaturalistic conditions. Granting the validity of both causal principles, the anchoring principle giving an advantage to starting with a high price (Ritov, 1996) and the traffic principle underlying the starting-low advantage (Ku, Galinsky & Murnighan, 2006), we nevertheless expected starting low strategies to produce higher endprices under FIFA 20 conditions. Two experiments, each using multiple copies of two players from the lowest price segment (Kramaric, Pizzi) and from an elevated price segment (Laporte, Martial), corroborated these expectations. A starting-low advantage was evident in two utility aspects, enhanced average (profit) and reduced variance (uncertainty aversion) of end prices obtained for player copies offered at lower starting prices. However, when the causal impact of the manipulated starting value was overshadowed by extraneous media influences, these findings were reduced or disappeared but never reversed.

Keywords: decision making, network traffic, anchoring, auction, low-high starting price, naturalistic data

Theory-driven approaches to predicting and optimizing performance in practical real-life settings have to face an intricate problem: Success on most tasks of realistic complexity depends on more than a single causal influence. Therefore, conflicts may arise between different theories that draw on different causal principles leading to different predictions and recommendations. Let us illustrate this common problem of applied or translational science (Bendoly & Clark, 2016; Fiedler, 2020) with regard to optimal strategies in dynamic competitive markets. If the goal is to maximize one's profit gained from selling some piece of property at the highest possible price, should one start with a high initial price to convey the classification of one's property as a precious high-quality good? Or should one start with a low price to highlight the chances to purchase an article that is not overly expensive?

In a frequently cited series of experiments, Ritov (1996) applied the theoretical notion of anchoring and insufficient adjustment (Epley & Gilovich, 2010; Mussweiler, Englich & Strack, 2004; Tversky & Kahneman, 1974) to auctions and found that setting a high starting anchor was the best strategy. Participants were divided into buyers and sellers, thus artificially creating a simulated competitive market. Transactions between buyers and sellers were completed through negotiations. In total 320 negotiations were recorded, and all but 14 of them resulted in an agreement. Results yielded that, higher values of initial offers, namely higher starting prices, led to higher values of a final agreement, and higher final prices.

The initial anchor value proved to be the best predictor of the obtained end price. However, setting a sufficiently high starting anchor is by no means the only viable principle to govern auctions.

More recent work by Ku, Galinsky, and Murnighan (2006) provided good reasons for an opposite strategy. They demonstrated that low starting prices at auctions were more likely to generate higher final prices than starting with a higher price. Several experiments were conducted in support of their hypothesis, but in this paper, we will only focus on the ones relevant to our hypothesis. The first experiment was performed in a simulated auction, with two groups, a low starting price vs. a high starting price. Results yielded that a lower starting price would lead to participants being more likely to make first and other bids and to make more total bids than the higher starting price. In the second study, data from the popular eBay market were collected on two different products, Persian rugs, and Nikon digital cameras. For each item auctioned the starting and final bid prices were recorded. Results showed that lower starting prices led to a higher chance for the auction to be completed, higher final prices, and significantly predicted higher traffic. In a third experiment, data on Tommy Bahamas' shirts were collected on eBay. In the low starting price group prices were set at \$10 and in the high starting group prices were set at \$25. Results not only showed that traffic mediated the relationship between starting and final prices, but also that low starting prices attract more initial bidders, leading to more (emotional) sunken costs and ultimately to a higher escalation of commitment to the bidding process.

The reasoning behind this notion is as follows: Low starting prices attract more buyers, reducing the monetary barrier of high starting prices. Consequently, more buyers generate more traffic in competitive mar-

Corresponding author: Andrei Popescu, Department of Psychology, Heidelberg University, Hauptstraße 47-51, 69117 Heidelberg, Germany. e-mail: andreipopescumdp@gmail.com

kets, which makes the auctioned object appear more desirable. Moreover, competition among many interested buyers causes psychological sunk costs, which in turn raises the buyers' emotional involvement. The authors conducted several experiments, five to be more precise, to test their hypothesis, both in virtual and offline surroundings. They received strong and consistent support for the advantage of starting low.

It is also both interesting and important to note the difference in anchoring effects in auctions and negotiations. Galinsky and colleagues (2009) detail in their paper that in negotiations a high-value anchor is consistent with its perceived evaluation, whereas auctions entail various social processes that can lead to higher final prices such as lower barriers of entry, increased number of bidders, increased sunken costs and increased the perceived value of the auctioned object.

Yet, juxtaposing the opposite predictions that Ritov (1996) and Ku and others (2006) derived and tested on theoretical and logical grounds is not meant to suggest that only one theory is correct. We assume that both theoretical principles are valid and logically compatible with each other; they simply deal with fully different stages of a temporally unfolding pricing process. The anchoring principle pertains to the starting price that affects the perceived monetary values within individual agents' minds, whereas the traffic principle refers to the dynamic process that takes place between many different bidders in an interpersonal competition process. Granting that both principles are theoretically sound and exert a predictable influence on auctions, the net outcome may point in the direction of the dominant principle. Apparently, the anchoring principle dominated in Ritov's (1996) lab experiments that rendered the numerical stimuli very salient but created little opportunity for traffic and interpersonal competition. Ku and colleagues (2006), in contrast, apparently succeeded in creating experimental setups that allowed the dynamic traffic principle to unfold and override the influence of the starting anchor. In support of Ku and colleagues (2006), Simonsohn and Ariely (2008) conducted a similar market analysis, by examining DVD sales on eBay. They discovered that low starting prices attract more bidders and result in higher selling prices. On the other hand, Ye and colleagues (2021) have constructed a data-driven regression analysis of online auctions that focuses on finding the best predictors of a successful auction, one of them being the starting price. Interestingly, their model suggests that a higher starting price might generate on average higher-end prices but attract fewer bidders, consistent with (Ariely & Simonson, 2003). In this case, a high starting price is mostly associated with a higher perceived value. Would this still apply if a buyer would inform themselves of the estimated value of the auctioned item beforehand? Or would low starting prices, lead as hypothesized by Ku and colleagues (2006) to higher final prices? This is one of the many reasons, why the FIFA 20 market offers unique research platforms, as most if virtually not all gamers, can check the current estimated value of the auctioned item on online platforms such as Futbin (2022).

Thus, in this paper, we would like to test the robustness of Ku and others (2006) in a different online, but real-world market. As mentioned above, when auctioning, players can gauge the estimated average value of a player at any time, so it would be interesting to see if low starting prices can still lead to higher selling prices in this context. Additionally, the same item can be found at different online vendors on the transfer market, giving sellers less freedom in manipulating the price of auctioned players to their advantage, as other people hold the same items with the same ingame value. Furthermore, at the time of writing this paper, no other study tested our hypothesis in a virtual market setting of this size, with millions of active gamers participating in the game worldwide. Therefore, due to the market's unique auction system (which will be detailed in the upcoming pages), its sheer size in volume, and its dynamics coupled with the lack of literature on this particular market setting, we believe our paper offers an incremented value to the scientific community.

Preview of the Present Research

Thus, predicting and controlling which one of two or more theoretical principles dominates the outcomes obtained in the real world depends not only on the validity of the theoretical principles but also on the structure of the applied setting, to which theories are applied. Regarding auctions, it is necessary to analyze the structure of the market in question concerning such issues as (a) utilities versus market prices, (b) the unique value of the auctioned goods, (c) the expected number of agents bidding for unique goods, (d) and the temporal course of the bidding process. Even when no universal theory is precisely tailored for the specific auction setting, it may be possible to understand why a specific real-life setting calls for a particular optimal strategy.

Illustrating this major issue in applied or translational research, the present research constitutes an attempt to study quasi-realistic auctions in the context of an existing virtual game market, FIFA 20, within which millions of people compete for unique targets, player cards, that represent a quantifiable and artificial in-game value of real football players.

It is important to mention, that the industry of video games has been exponentially growing in the last decade, and it is forecasted to grow by 12.9% yearly, from 2022 to 2030. At the time of writing this paper, the estimated value of the gaming industry as of 2021 is $195.7 billion (GVR, 2022). Furthermore, FIFA 20 makes it possible to investigate the findings of Ritov (1996) and Ku and colleagues (2006) in a *real* market, with real monetary and emotional investment of the consumers. The game does not only generate revenue by its retail price, but it also gives gamers the enticing option of buying with *real* money in-game currencies that they can use to further improve their virtual team. Furthermore, the FIFA series games are notoriously competitive, and regularly host tournaments, some with price pools of $350,000. Thus, the platform of FIFA 20 guarantees the authenticity of the collected data and further reinforces the robustness of the (low) starting prices and (high) traffic in auction-based markets.

In FIFA 20, participants can play the role of a soccer manager who can buy and later sell major international soccer players using in-game currencies (virtual coins). The players are displayed as game cards. Given that a huge number of people participate and most of them are motivated to be clever and successful managers in soccer and given that the players' names belong to existing unique soccer stars and idols, the FIFA 20 market can be characterized as follows. It relies on market prices rather than predetermined utilities, and it is dynamic and characterized by high traffic caused by many competitors bidding for unique favorite players. Consequently, the traffic principle can be expected to overshadow the initial anchoring effect, such that starting low affords a superior strategy.

Specifics of the Transfer Market. Important for understanding and predicting the FIFA market is the so-called countdown effect; auction traffic drastically increases during the last few minutes or even seconds before the expiration time of the player, which can be constantly monitored from the beginning until the end of the auction. It is not uncommon that a player's first bid would be placed during the last minute before the expiration time. It is usually then when other gamers heavily engage in bidding.

The present research constitutes a new attempt to investigate the question that motivated opposite answers by Ritov (1996) and then by Ku and others (2006). Exploiting the dynamics and the realistic complexity of a well-established virtual market game, we aim to investigate the impact of starting low on the final price obtained for distinct soccer players.

Due to several reasons such as the dynamics and the enormous traffic of this game market, the uniqueness of soccer players, and the dependence of their value on quickly changing market prices, we expected that multiple influences might affect the players' selling price. Still, as a theoretical default, low starting prices should lead to higher final prices, mediated through high traffic and dense competition. Given the huge traffic potential of FIFA 20 and given the factor of "major players "(dealers, or traders in the field, who have access to large sums of virtual coins and buy hundreds if not thousands of players), we expected to find, if anything, support for the starting-low principle in a semi-naturalist research setting that promises to improve on the external validity of previous auction research.

How the Transfer Market in FIFA 20 Works

The FIFA 20 game was produced by EA Entertainment, first released in 1993. By 2019, it had already sold over 282.4 million copies (Electronic Arts, 2019). An overly popular gaming option it offers is Ultimate Team, where the user can build a team of their choice using players from all around the world. In the last couple of years, the virtual Transfer Market has become more and more popular. It mimics the eBay market, where users can list the price of their own players to obtain virtual coins, which can be used in turn to buy other players or in-game consumables.

The transfer market is the game variant focused on in our study. As in a real market, both market-specific information and dynamic events can increase or decrease the simulated soccer players players' prices. For instance, if a player has an above-average performance during a real-life fixture (such as scoring a hat trick during a game), he has a high chance to be included in FIFA 20's *team of the week*. As the name suggests is an artificial in-game starting eleven composed of the best players (usually from major European leagues) in the respective week, according to their real-life performance. Therefore, if player X is included in the "team of the week", he will receive an additional game card with an overall better value and often, if not always, more expensive than his base card (the card he got at the release of the game). As the game progresses, more and more special cards of the world's best players are being released ("team of the week" being just one of the many events where special, better cards of the players are made available for a *limited* amount of time), the price of older cards decreases over time, while the price of newer cards (which become better and better as the game reaches its yearly end) increases. The time these cards are available in game packs, which players can purchase with in game currencies or with real money is limited. Hence, once they are no longer available, players are forced to acquire them on the transfer market, if they desire that specific player card. Thus, players are motivated to keep playing the game actively and make wise investments in buying and selling players, as they do not wish to make a loss.

Multiple copies of the same player are available; that is, there is not a single Cristiano Ronaldo or Lionel Messi player card available. Still, the prices of all copies of a player increase with the original's scarcity; the lower the probability to obtain him from a pack, which offers various player cards of different rarity and market value, the higher his market price. For example, at the time of writing this article, Manuel Neuer's base card's value was estimated to be roughly 30,000 coins, whereas Lionel Messi's would sell at around 343,000 coins. (FUTBIN, 2022)

As in a real-life market, prices are highly volatile, and sensitive to in-game events that can have sudden and unpredictable influences on resulting prices. Prices depend on whether better versions of certain

Figure 1. Example of a player (Niklas Süle) listed on the transfer market.

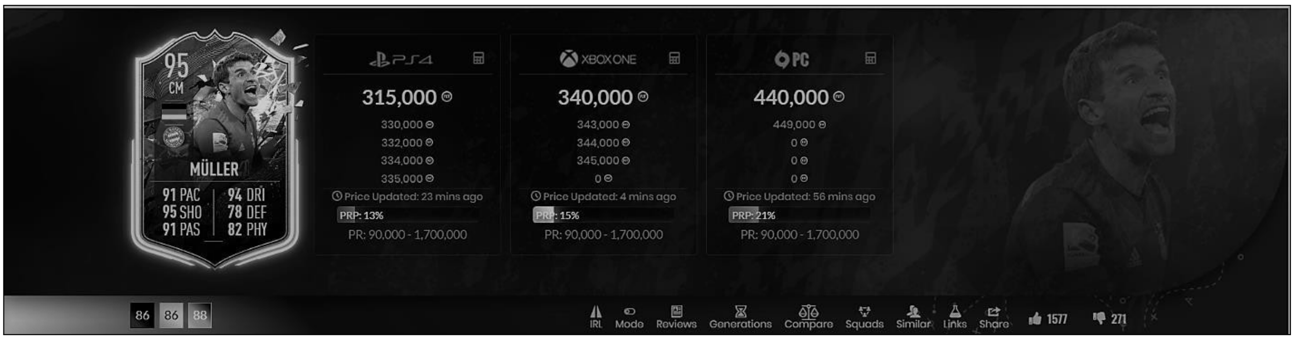

Figure 2. Illustration of player price fluctuations in Futbin.

players are being released when the performance of the analogous real-life player excelled. The market dynamics heavily also rely on millions of bidders, who actively participate in the game. Shortly after being released in September 2019, EA Games, the producers, posted a message stating that over 10 million copies had been sold so far on all platforms (PlayStation 4, XBOX, PC and Nintendo Switch). Players can be listed at any chosen price, yet in most cases the prices are naturally constrained by the current market value. Apart from the bidding option, players can be purchased via the buy-now method. Thus, if users want to circumvent the auctioning procedure, which always starts at a lower price than the buy-now price, they have the option to buy directly.

A start bidding price and a buy-now price can be determined in the range of 650 coins to 15,000,000 coins. Naturally, if a player's estimated worth is around 1 million coins and if someone chooses to list another version of the player at double the price, the chances of someone buying the more expensive player are exceptionally low. Not only the price but also the time period during which players remain on the market can be manipulated within a range from one hour to three days. Figure 1 depicts the format in which players are listed on the transfer market.[1]

As mentioned before, players are highly motivated to not bid randomly, but make careful, calculated decisions in the highly competitive game. Players participate in different weekly tournaments or daily rank-based matches, where winning or losing influences their potential rewards and placement in skill-oriented online rankings and divisions. It is also no surprise that teams with more expensive players increase their likelihood of winning. Gamers can also buy virtual coins with real money to acquire player packs, earning them player cards they can keep or sell if they do not need them or when they become outdated (as newer options are becoming available and affordable). Thus, a player's value changes over time, as seen in Figure 2, which illustrates the price fluctuations of the estimated value of a sample player in Futbin, namely, the German player Thomas Müller.

Given that many gamers invest real-life money to acquire better players and have better performances during the online weekly tournaments it becomes evident that the auctioning process in FIFA is of utmost priority to them.

Experiment 1a

Method

The following experiments (1a and 1b) can and should be regarded as individual and separate, as no interac-

[1]Concerning copyright issues when using screenshots from video-games in the context of research, see Lastowka and Ogino (2014).

tion effects between the two of them were expected or hypothesized. As the market at that time provided a finite number of players that can be bought and auctioned, coupled with the difficulties of auctioning multiple copies of the same player in an almost identical time frame and a limited number of funds, we have convened that 40 copies per player would suffice to prove the hypothesis.

To experimentally test the guiding hypothesis, N_1 = 40 identical copies of one player, Kramaric were bought. Kramaric as well as Pizzi from Experiment 1b were available at remarkably cheap prices. To deal with price variations during different periods of the day, all copies of Kramaric were listed in the morning. To rule out the complicating influence of gamblers using the buy-now option, the listing price for all copies was set to a much higher value than their current market value, namely 10,000 coins. The estimated current values, 1,600 coins for Kramaric, was determined using the online platform Futbin.

Table 1. Design overview of Experiment 1a.

Starting low Kramaric = 700
Starting high Kramaric = 1,000

The 40 copies of Kramaric were subdivided into two experimental groups that were assigned either a low or a high starting price, respectively. The low starting price for Kramaric was set at 700 coins. The low starting price of 700 coins is the lowest possible that the game allows for both players. The high starting price was selected as high as possible, by averaging 40 random high prices of copies of Kramaric listed on the market by other gamers at that time (that is 50% of the players' estimated value) in order to choose adequate prices to match our competitors, as one would do in a real market setting. Hence, we devised a 2x2 design, with low and high starting prices for Kramaric.

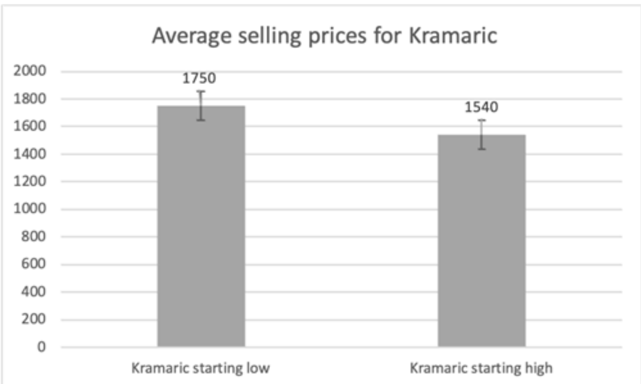

Figure 3. Average final prices for Kramaric by condition. Error bars indicate the standard error of the mean.

The selling prices obtained for these players in different experimental conditions constitutes the dependent variable. (For convenience, we report uncorrected selling prices rather than differences between selling and buying prices, because we are merely interested in the relative success of different starting values.

Results

As evident from Figure 3, the average selling prices indeed supported the notion that the superior strategy is, if anything, to start low. A t-test assuming unequal variance was performed. The selling-price difference between the starting-low and the starting-high condition was significant for Kramaric ($M_{low} = 1,750$, $SD = 100$ vs. $M_{high} = 1,540$, $SD = 223$), $t(38) = 3.8$, $p < .001$, $d = 1.3$.

All data sets were tested for homoscedasticity and in In Kramaric's case, we noticed the data was heteroscedastic, after testing to see if it violates the homoscedasticity assumption ($p < .001$). This was expected for our data sets, as the difference in the independent variable, the starting price is quite substantial between the two groups. Although the t-test is a rather robust test, we chose to conduct a robust linear regression analysis, with the independent variable being the high and low starting prices and the dependent variable, being the final prices of both groups. We used the Huber-White's Robust Standard Errors approach, where the standard errors become heteroskedasticity-consistent (Hayes & Cai, 2007). As expected, the p-value was highly significant ($p < .001$), showcasing once that the starting price is a robust predictor of the final price.

Experiment 1b

Method

$N_2 = 40$ copies of another player, Pizzi, were bought. They were listed two weeks later for one hour when their price had risen due to increased demand. To deal with price variations during different periods of the day, the copies of Pizzi in the evening, as opposed to listing them in the morning, as we did with Kramaric. The main reason is, that given the huge gamers base (millions) and the competitive aspect of the game, we wanted to avoid confounding variables such as time-driven increased active players (that means more players playing FIFA 20 in the evening or morning on a specific day due to in-game events etc.) Given the highly dynamic environment of the virtual market of FIFA 20, it makes the setting unpredictable. Thus, in order to preserve the validity of the collected data, we decided to auction the copies of Pizzi at a different time. To rule out the complicating influence of gamblers using the buy-now option, the listing price for all copies was set to a much higher value than their current market value, namely 10,000 coins. The estimated current values, 3,800 coins, were determined using the online platform Futbin. One copy of Pizzi was bought via the "buy now" method, so it was removed from our experiment.

The 39 were subdivided into two experimental groups that were assigned either a low or a high starting price, respectively. For Pizzi the low starting price was set at 700 coins and the high starting price at 3,000 coins. The low starting price of 700 coins is the

Table 2. Mean and variance of selling prices for Kramaric and Pizzi in Experiment 1.

	Kramaric (n = 40)		Pizzi (n = 39)	
	Starting low	Starting high	Starting low	Starting high
Sample size	20	20	19	20
Mean selling price	1750	1540	4511	4425
Two-tailed contrast	$t(df = 37) = 3.84, p < .001$		$t(df = 38) = 0.45, p = .65$	
Standard deviation (Uncertainty)	100	223	373	755
Two-tailed variance contrast	$F(19, 19) = 4.99, p < .001$		$F(19, 18) = 4.10, p = .002$	

lowest possible that the game allows for both players. High starting prices were selected as high as possible, by averaging 40 random high prices of copies of Pizzi listed on the market by other gamers at that time (that is > 50% of the players' estimated value) in order to choose adequate prices to match our competitors, as one would do in a real market setting. Hence, we devised a 2x2 design, with low and high starting prices for Pizzi.

The selling prices obtained for these players in different experimental conditions constitutes the dependent variable. For convenience, we report uncorrected selling prices rather than differences between selling and buying prices, because we are merely interested in the relative success of different starting values.

Table 3. Design overview of Experiment 1b.

Starting low Pizzi = 700
Starting high Pizzi = 3,000

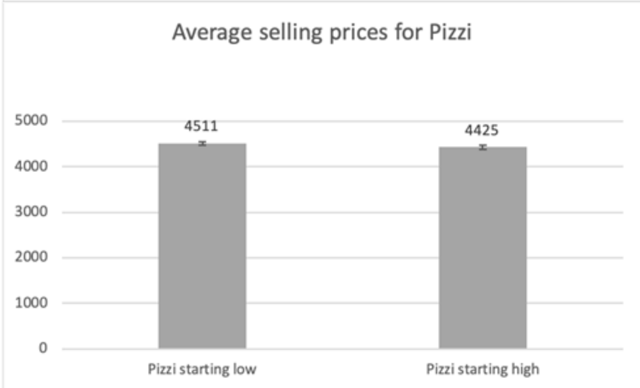

Figure 4. Average final prices for Pizzi by condition. Error bars indicate the standard error of the mean.

Results

As evident from Figure 4, the average selling prices indeed supported the notion that the superior strategy is, if anything, to start low. A t-test assuming unequal variance was performed. The selling-price difference between the starting-low and the starting-high condition was significant for Kramaric ($M_{low} = 1,750$, $SD = 100$ vs. $M_{high} = 1,540$, $SD = 223$), $t(38) = 3.8$, $p < .001$, $d = 1.21$. The results for Pizzi pointed in the same direction ($M_{low} = 4,511$, $SD = 372$ vs. $M_{high} = 4,425$, $SD = 755$) but the difference for Pizzi was not statistically significant, $t(37) = 0.45$, $p = .65$, $d = 0.14$, obviously due to a ceiling effect (i.e., generally inflated selling price).

Discussion for Experiments 1a and 1b

Note that the advantage of the starting-low over the starting-high condition is exclusively a matter of selling prices, disregarding the difference in starting value. For both players, the relative increase in market value is clearly higher when it starts low; this is particularly the case for Pizzi, for whom roughly the same selling price was obtained although the initial price in the starting-low condition was 2,000 lower than in the starting-high condition. (However, the focus of the present research is only on the end price).

Furthermore, the subjective utility of starting with a lower price also led to a reduced uncertainty aversion, inherent in the variation of copies auctioned with a low starting price. Table 1 shows that this advantage was evident for both Kramaric and Pizzi.

Thus, the results of the first experiment provide moderate support for the advantage of starting low, rather than high, in a competitive market as dynamic and as volatile as FIFA 20. Although the difference in the end price obtained with both strategies was only significant for one player, Kramaric, starting low consistently reduced the variation in the obtained end price for both players, thus creating an additional advantage in terms of lesser uncertainty aversion. To be sure, the higher variance of the starting-high strategy also means that high starting prices produced the most auspicious outliers. Indeed, the fortunate outcomes (defined as average price plus one standard deviation) for Pizzi were higher in the starting-high $(4,425 + 755)$ than in the starting-low condition $(4,511 + 373)$. However, the most extreme outcomes, or outliers, must not be confused with the expected outcomes, which never favored the starting-high condition.

Still, we must face the unequal results for Kramaric and Pizzi. In the absence of an unequivocal explanation, we can think of two reasons for inequality. First, the occasional success of starting high might be contingent on the auction process overcoming a threshold; starting high success relies on bidders who are not discouraged by a high entry threshold. Second, the difference may reflect extraneous influences of gossip and news associated with the original soccer players. Thirdly, in the case of Pizzi the effect size has substantially decreased. Unfortunately, the evidence from Experiment 1 do not provide us with cogent evidence about the viability of these two accounts.

Experiment 2

To cross-validate and extend the results obtained in Experiment 1, we conducted a second experiment supposed to overcome two limitations. First, we wanted to rule out the possibility that the results for Kramaric and Pizzi were particularly cheap players available at a dumping-price level. We, therefore, conducted a similar experiment with two players from a higher price segment. Second, we wanted to clarify the mediating process of the starting-low advantage, particularly the potential role of enhanced traffic solicited by a low starting price. Toward this end, we assessed the offers for both players every 30 or every 60 minutes if they were listed for 6 or 12 hours, respectively. Enhanced traffic solicited by starting low should be reflected in more frequent offers. Alternatively, a "countdown effect" suggests that virtually all traffic takes place in a concentrated bidding process during the last few minutes. Thus, traffic may not reflect the frequency of competition but rather the concentrated dynamics of short-term competition during the last minutes. Like experiment 1, we divided experiment 2 into two subsets, to ease understanding and overview of the results. Given that we conducted our experiments with a limited number of funds, again, we chose to buy 40 copies of each player.

Regarding traffic, unfortunately, due to the exponential increase in the number of bids during the countdown effect, it is virtually impossible to keep track of all the bids without log entries, which are not available to the player. The experimental subsets can and should be regarded as individual and separate, as no interaction effects between the two of them were expected or hypothesized. Table 4 emphasizes the overall design overview of experiment 2, encompassing both experimental subsets a and b.

Experiment 2a

Method

A new player was chosen for Experiment 2 from a higher price range. The chosen player was Aymeric Laporte, originally evaluated at $18,000$ coins. Forty copies of Laporte ($N_1 = 40$) were bought and were again subdivided into two experimental conditions, starting low versus starting high. Thus, 20 copies of each player were assigned to the low starting price group and the rest of the 20 copies were assigned to the high starting group. The low starting price was set to the minimum possible at that time, namely $2,400$ coins. The high starting price was set to 50% of the evaluated price, namely $9,000$ virtual coins. A different high price cutoff was set this time compared to the first experiment to test the robustness of the "low starting price $\geq$ increased traffic $\geq$ high final prices" hypothesis. To prevent gamers from buying copies Laporte via the buy-now option, the buy-now price is set to a higher level than their evaluated price, namely, $45,000$ coins. We wanted to see whether low starting prices would still lead to higher final prices when players listed on the market were more expensive.

To assess traffic, we modified the procedure in the following ways. Unlike an eBay market, there are no data logs available in FIFA 20 to see how many bids have been placed for each player individually. Only the highest bid price was shown at a time, making it virtually impossible to monitor all bids placed on the 40 individual player copies. Thus, players in both the low and high starting price conditions were further divided into two equally large subgroups. Half were listed for six hours whereas the other half was listed for 12 hours, as evident from the design overview in Table 2. The twenty copies of Laporte, which were listed for six hours each, were checked every 30 minutes, and the other twenty copies which were listed for 12 hours, were checked hourly, to monitor how the traffic and the bidding price varied over time. If bidding prices did change, we merely counted how many times the price changed for each individual player. For example, should the initial bidding price of a player change three times before it expired, the player's counter would indicate 3.

Results

A significant end-price difference between the starting-low and the starting-high condition was only obtained for Laporte (see Figure 5 and Table 2), favoring the starting-low strategy, $M_{low} = 16,110$, $SD = 1,765$ versus $M_{high} = 14,652$, $SD = 6,873$), $t(36) = 2.3$, $p = .02$, $d = 0.83$ (Figure 4).

Regarding the traffic, only the starting low group generated any bids, outside of the 1-minute period (narrow bidding period), when the "countdown" effect sets in motion. For the starting high group, outside of this narrow bidding window, for a total of 20 players, only 1 bid was placed. Figure 5 depicts the number of bids placed for the 20 players of each group. "Series 1" displays the number of bids for the low starting group and "Series 2" for the high starting group. Not taking into account the bids placed in the narrow bidding period occurring during the countdown effect, our results are congruent with our initial hypothesis, that low starting prices lead to increased traffic and result in higher-end prices.

Experiment 2b

Method

Just like experiment 2a, a new player was chosen for Experiment 2 from a higher price range. The chosen player was Antony Martial, originally evaluated at 12,000 coins. Forty copies of Martial ($N_2 = 40$) were bought and were again subdivided into two experimental conditions, starting low versus starting high. Thus,

Figure 5. The number of bids for bids per player copies in the low starting group, and high starting group.

20 copies of each player were assigned to the low starting price group and the rest of the 20 copies were assigned to the high starting group. The low starting price was set to the minimum possible at that time, namely 800 coins. The high starting price was set to 50% of the evaluated price, namely 6,000 virtual coins. A different high price cutoff was set this time compared to the first experiment to test the robustness of the "low starting price => increased traffic =>high final prices" hypothesis. To prevent gamers from buying copies of Martial via the buy-now option, the buy-now price is set to a higher level than their evaluated price, namely, 45,000 coins. We wanted to see whether low starting prices would still lead to higher final prices when players listed on the market were more expensive.

To assess traffic, we modified the procedure in the following ways. Unlike an eBay market, there are no data logs available in FIFA 20 to see how many bids have been placed for each player individually. Only the highest bid price was shown at a time, making it virtually impossible to monitor all bids placed on the 40 individual player copies. Thus, players in both the low and high starting price conditions were further divided into two equally large subgroups. Half were listed for six hours whereas the other half was listed for 12 hours, as evident from the design overview in Table 3. The twenty copies of Martial, which were listed for six hours each, were checked every 30 minutes, and the other twenty copies which were listed for 12 hours, were checked hourly, to monitor how the traffic and the bidding price varied over time. If bidding prices did change, we merely counted how many times the price changed for each individual player. For example, should the initial bidding price of a player change three times before it expired, the player's counter would indicate 3.

Results

Although the results for Martial pointed in the same direction ($M_{low} = 12,792$, $SD = 1,974$ versus $M_{high} = 12,142$, $SD = 2,548$), the difference did not approach a conventional level of statistical significance, $t(36) = 0.9$, $p = .37$, $d = 0.33$ (Figure 6).

Because a special in game event was released during our experiment (which will be later detailed in the "Limitations" section of the "General discussion") all copies of Anthony Martial sold out almost instantly at the "Buy now" price. Thus, no bids could be placed in any of the two groups, making the recorded traffic for this player 0.

All data sets were tested for homoscedasticity. Again, as was the case in the first experiment, the significant difference in starting price for Martial made our data heteroscedastic upon testing ($p = .02$). As before, we conducted a robust linear regression analysis, with the independent variable being the high and low starting prices and the dependent variable, being the final prices of both groups. We used the Huber-White's Robust Standard Errors approach, where the standard errors become heteroskedasticity-consistent (Hayes & Cai, 2007).

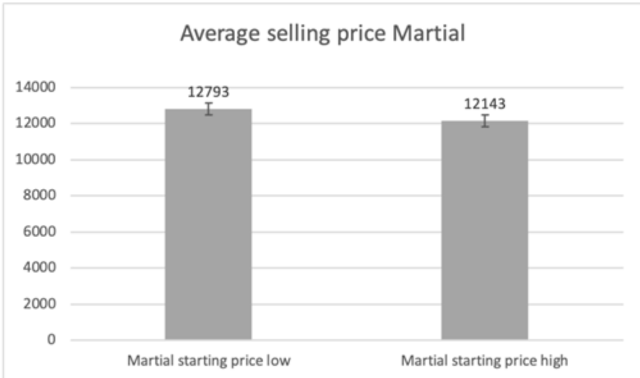

Figure 6. Average selling prices (and standard errors) Martial.

Discussion for Experiments 2a and 2b

Table 4 reveals that the end-price variation was again somewhat reduced in the starting-low condition, although the variance difference was less pronounced than in Experiment 1 and not quite significant statistically. Nevertheless, both utility indicators, high average end price and the low variance reducing uncertainty aversion, if anything, point to starting low as the superior strategy. However, again, in a multicausal market, the starting-low advantage can be obscured when extraneous causal influences create an imbalance in the experimental design.

To figure out what extraneous influence might have precluded the predicted difference for the second player, Martial, we first speculated whether the unequal listing time (6 vs. 12 hours) may have contributed to the asymmetry. The most plausible interpretation, though, is in terms of extra-auction events. Given the prominence of both players, the media context of Experiment 2 provided us with some supportive evidence for the notion that extraneous news about the original players may account for the diluted results for Martial. During the time of the experiment, copies of

Table 4. Means and Variance of selling prices for Laporte and Martial in Experiment 2.

	Laporte (n = 40)		Martial (n = 40)	
	Starting low	Starting high	Starting low	Starting high
Sample size	20	20	20	20
Mean selling price	16,100	14,652	12,792	12,142
Two-tailed contrast	$t(36) = 2.3, p = .03$		$t(36) = 0.9, p = .40$	
Standard deviation (Uncertainty)	1,764.79	2,173.55	1,973.66	2,547.77
Two-tailed variance contrast	$F(19, 19) = 1.5, p = .20$		$F(19, 19) = 1.7, p = .10$	

Anthony Martial, who was listed for 12 hours on the transfer market, were instantly bought in a matter of seconds. All copies of Anthony Martial on the market had gone extinct, as they were all bought via the "buy now" option in spite of us setting the highest price possible. The explanation was simple. During the final stage of the experiment, a special event was released that greatly increased the market value of Martial as a desired player. This will be later addressed in the "Limitations" section of our study. Thus, the divergent results seem to reflect the impact of extraneous anomalies. The dramatic extinction of Anthony Martial copies apparently leveled off the differential impact of starting prices on size but also on the variance of end prices.

Experiment 2 also sheds some light on an observation that confirmed our previous experience with the FIFA 20 market. Prior to the experiments, we had made several small tastings on the market in order to understand its mechanisms and noticed that the highest prices can often be achieved through a third option, the buy-now method. Namely listing players at a value equal to or slightly lower than their current value (a couple hundred or, for more expensive players, thousands of coins) often resulted in fast, almost immediate selling of the players, more than usual at a higher price, should the player have been bought through the bidding option. In the case of Anthony Martial, his maximal buy-now prices and market value coincided. Thus, when demand rose, he got instantly bought with no regard to the bidding price. This happened for 16 out of a total of 40 player copies.

Regarding traffic, there was indeed a tendency of starting low to generate more traffic than starting high. However, this tendency was the only significant test in the case of Anthony Martial, $t(20) = 7.88$, $p < .001$, $d = 0.78$. For Aymeric Laporte, no bids were placed before the final minutes of the auction, regardless of the low or high starting price. Again, this finding suggests that extraneous constraints of the multi-causal transfer market may overshadow the traffic principle as it was originally understood by Ku and colleagues (2006). Yet, despite these intricacies and anomalies, our findings corroborate the notion that, provided the impact of starting strategies is not overshadowed by extraneous causal influences, the starting low is superior to a starting-high strategy in the dynamic FIFA 20 market game.

General Discussion

Limitations

One of the first limitations we encountered was a financial one. In order to conduct the experiments, a FIFA account had to be created. With only limited funds at our disposal, both virtual and real currencies, we could not afford to buy more than 40 copies of each player.

During our second experiment, the creators of FIFA 20, EA SPORTS, released a special in-game event, an SBC (squad building challenge), where gamers were asked to build various fictional teams matching certain criteria, like players belonging to a certain nationality or club. The reward for completing this SBC was a high-rated, sought-after player. Antony Martial was a perfect candidate for completing this SBC, as gamers were required to include French and Manchester United players in their squad. At the time of conducting our second experiment, Antony Martial, a French player, was playing for Manchester United. This event skewed our in-group differences between starting low and starting high groups and made it impossible to record any bids, as most copies available in the entire online market were sold out in a matter of minutes.

An important point worth mentioning is the constraints of field studies. For instance, in the first experiment, we auctioned copies of Pizzi and Kramaric at different hours of the day in order to avoid time effects that might alter the bidding such as SBCs (squad building challenges), server disruptions (which were not unusual during the pandemic), ongoing online competitions and so on. Thus, it made more sense for us, to be cautious for our first experiment and take these possibilities into consideration. Additionally, when listing the copies of one player, all copies must be listed at approximately the same time, to avoid the possible time effects mentioned above.

Another limitation of our field study represents the technical constraints of the FIFA 20 market, which like a real market, it is subject to certain regulations. In this case, prices could not be set lower than 700-800 virtual coins for any player or higher than 14000 coins for Antony Martial (due to his increased demand, a price cap was set to limit potential price abuses). Another difficulty related to prices was choosing a cutoff for the lower and high, star2ng prices. Unfortunately, Ku and colleagues (2006) do not provide any method on how to choose them. We believe that further research is needed to address this issue.

We would also like to address the violation of the homoscedasticity assumption which occurred twice, for Kramaric and Pizzi. Given the nature of our study, i.e., a field study which is working with big variations of the independent variable (starting prices) between groups, such an occurrence was expected. For this reason, we conducted the robust linear regression, to emphasize that the heteroscedasticity of our data does not interfere with the strong relation between starting and final prices, a fact most literature concerning auctions agrees on (Ye et al., 2021).

One other limitation, which is not atypical for field studies, is the difficulties of replicating our findings. In our case specifically, the servers of FIFA 20 shut down with the appearance of the newer FIFA games. Additionally, the experiment took place in 2020 at the height of the pandemic, thus any future studies on this topic will most likely not be able to be conducted in the same social framework.

Concluding remarks

As suggested at the outset, in a multi-causal world, different causal influences are not mutually exclusive. For instance, in a dynamic market setting, starting with a high anchor and enhanced traffic due to starting low may both increase the final selling price in an auction. The net influence of both opposite influences depends on the task environment giving more weight to anchoring effects or the traffic principle. (Ritov, 1996) argues that the starting price in an auction serves an anchoring effect, while Ku and colleagues (2006) emphasize the importance of traffic and that (in certain scenarios, such as a virtual market) the anchoring effect can be reversed. As seen in our study, the findings of both (Ritov, 1996) and Ku and others (2006) can coexist. The FIFA 20 market plausibly constitutes a task set that gives less weight to anchoring than to the traffic. Because the price of different soccer players varies by magnitudes, fanning up a huge range of simultaneous anchors, it seems unlikely that a relatively low or high initial anchor for a specific soccer player determines the auction of specific price levels. Conversely, because FIFA 20 constitutes an inherently dynamic market environment, it is not too surprising that enhanced traffic fostered by low starting prices is a chief determinant of the players' end prices.

The evidence gathered in the present research under quasi-naturalistic conditions is largely consistent with this contention, but only under default conditions, as long as no extraneous causal influences complicate and overshadow the competition of starting-low and starting-high strategies. Our experiments with multiple copies of four rather well-known soccer players – Kramaric, Pizzi, Laporte, and Martial – have shown that extraneous episodes related to the original players in the media can come to dominate their starting value within the auction, testifying to the vicissitudes of the multi-causal world. Consequent to our hypothesis, a reversed anchoring effect was found, contrary to the findings of (Ritov, 1996). But we also found an unexpected effect of increased variance in the high final prices group, making it an interesting question for any follow-up studies, as to why such a phenomenon can occur in a virtual market setting. Nevertheless, in the absence of such extraneous events overriding the outcomes of soccer-player transactions, our findings demonstrate the superiority of starting low in those cases in which the starting value does exert a substantive influence on the end price. This (conditional) advantage of the starting low is not only manifest in an enhanced average end price but also in reduced uncertainty aversion.

Fortunately, the FIFA games series is very popular and has seen 30 annual publications since its first release in 1993. Thus, future market research in the online markets of the Fifa games should be easily accessible and feasible. From our present research, we present the following ideas of future research. For once, if more funds are available, we recommend buying more than 40 copies per player, in order to have a bigger pool of investigates players. Secondly, it would be interesting to record the screens during the bidding process, especially during the countdown window, and manually count all bids, after the auction is concluded. This would give a more accurate representation of the differences in traffic between starting low and starting high groups. Thirdly, if again, more funds are available at the disposal of the authors, more expensive desirable players should be bought and auctioned, as they have more added value to the players and are scarcer, thus likely leading to bigger price discrepancies between the experimental groups.

Lastly, the variance of each group should also be taken into account, namely in trying to uncover whether there is a correlative link between an increased variance and an increased price of the player. We suspect that players in the higher-price echelons, due to their scarce availability, may be auctioned for prices significantly different than their average price displayed on Futbin, mainly due to their inconsistent market availability.

We would also like to point out the absence of any conflict of interest. The collected data is categorized as naturally occurring data sets (NODS), as it is pointed out (Wendt, 2020). To quote Goldstone and Lupyan (2016, 1), NODS are "patterns of website links, dictionaries, logs of group interactions, collections of images and image tags, text corpora, history of financial transactions, trends in twitter tag usage and propagation, patents, consumer product sales, performance in high-stakes sporting events, dialect maps, and scientific citations" (page 1). Additionally, other platforms (FUTBIN, 2022) use gamers' data from the FIFA franchise series and display it online, for free access.

We would like to conclude, by drawing the most important decision rules for (online) auctions derived from our study:

- If starting prices are low, then they attract more early bidders.
- If starting prices are low, they generate higher-end prices.
- If starting prices are high, they generate an increased final price variance, with both high and low ceilings.

Acknowledgements: This research was supported by Grant Fi 294/ 30-1 awarded by the Deutsche Forschungsgemeinschaft to the second author.

Declaration of conflicting interests: The authors declare no conflicts of interest.

Peer Review: In a blind peer review process, Alica Mertens and Wolfgang Schoppek have reviewed this article before publication. All reviewers have approved the disclosure of their names after the end of the review process.

Handling editor: Alexander Nicolai Wendt

Citation: Popescu, A. & Fiedler, K. (2023). Anchoring and traffic effects in the virtual market platform of FIFA 20. *Journal of Dynamic Decision Making, 9*, Article 2. doi:10.11588/jddm.2023.1.88639

Received: 18.04.2022
Accepted: 13.04.2023
Published: 18.12.2023

References

Ariely, D. & Simonson, I. (2003). Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions. *Journal of Consumer Psychology*, *13*, 113–123. https://doi.org/10.1207/S15327663JCP13-1&2_10

Bendoly, E. & Clark, S. (Eds.). (2016). *Visual analytics for management: translational science and applications in practice*. Taylor & Francis.

Epley, N., & Gilovich, T. (2010). Anchoring unbound. *Journal of Consumer Psychology*, *20*(1), 20–24. https://doi.org/10.1016/j.jcps.2009.12.005

Fiedler, K. (2020). Grounding applied social psychology in translational research. In J. P. Forgas, W. D. Crano, & K. Fiedler (Eds.), *Applications of social psychology: How social psychology can contribute to the solution of real-world problems* (pp. 23–39). Routledge/Taylor & Francis Group. https://doi.org/10.4324/9780367816407-2

Electronic Arts. (2019). [Website of the Video Game FIFA 2020]. Retrieved January 1, 2020, from https://www.ea.com/games/fifa/fifa-20

FUTBIN. (2022). [Website of the Futbin organisaton]. https://www.futbin.com/

Galinsky, A. D., Ku, G., & Mussweiler, T. (2009). To Start Low or To Start High? The Case of Auctions Versus Negotiations. *Current Directions in Psychological Science*, *18*, 357–361. https://doi.org/10.1111/j.1467-8721.2009.01667.x

Goldstone, R. L. & Lupyan, G. (2016). Discovering Psychological Principles by Mining Naturally Occurring Data Sets. *Topics in Cognitive Science*, *8*(3), 548–568. https://doi.org/10.1111/tops.12212

GVR (2022). *Video Game Market Size, Share & Trends Analysis Report By Device (Console, Mobile, Computer), By Type (Online, Offline), By Region (North America, Europe, Asia Pacific, Latin America, MEA), And Segment Forecasts, 2022 – 2030*. https://www.grandviewresearch.com/industry-analysis/video-game-market#

Hayes, A. F. & Cai, L. (2007). Using heteroskedasticity-consistent standard error estimators in OLS regression: an introduction and software implementation. *Behavior Research Methods*, *39*, 709–722. https://doi.org/10.3758/bf03192961

Ku, G., Galinsky, A. D., & Murnighan, J. K. (2006). Starting Low but Ending High : A Reversal of the Anchoring Effect in Auctions. *Journal of Personality and Social Psychology, 90*, 975–986. https://doi.org/10.1037/0022-3514.90.6.975

Lastowka, G. & Ogino, C. (2014). Use of Video Game Screenshots in Scholarly Publications: Recommendations from the Digital Games Research Association. http://www.digra.org/wp-content/uploads/digital-library/ScreenshotsFairUseRecommendations_DiGRA.pdf

Mussweiler, T., Englich, B., & Strack, F. (2004). Anchoring effect. Cognitive illusions: A handbook on fallacies and biases in thinking, judgement and memory. In R. F. Pohl (Ed.), *Cognitive Illusions. A Handbook on Fallacies and Biases in Thinking, Judgment and Memory* (pp. 183–200). Psychology Press.

Ritov, I. (1996). Anchoring in simulated competitive market negotiation. *Organizational Behavior and Human Decision Processes*, *67*(1), 16–25. https://doi.org/10.1006/obhd.1996.0062

Simonsohn, U. & Ariely, D. (2008). When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay. *Management science*, *54*, 1624–1637. https://doi.org/10.1287/mnsc.1080.0881

Tversky, A. & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Wendt, A. N. (2020). The qualitative face of big data: Live streaming and ecologically valid observation of decision-making. *Journal of Dynamic Decision Making*, *6*, Article 3. https://doi.org/10.11588/jddm.2020.1.69769

Ye, Q. C., Rhuggenaath, J. S., Zhang, Y., Verwer, S. E., & Hilgeman, M. J. (2021). Data driven design for online industrial auctions. *Annals of Mathematics and Artificial Intelligence*, *89*, 675–691. https://doi.org/10.1007/s10472-020-09722-2