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AUCTIONS: THE CHOICE TO BUY-IT-NOW

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Abstract

The features of an auction and how parties utilize them dictate the outcome of the auction. One of these features is the "Buy-It-Now" price – the option to pay a full, fixed price for an item set by the seller instead of bidding for it. The presence of this functionality was studied and proven to increase the revenue of the seller. However, the existing literature focused on a specific type of auction, namely sealed-bid auction. This thesis investigates whether this result holds under a different auction environment and how a different auction type impacts the Buy-It-Now price.

We study what the effect is under different auction environments – during an open-bid auction where all information is disclosed and during a sealed-bid auction where the identities and bids of the buyers are hidden. We conduct 6 auction sessions with 72 participating students and cannot conclude that the type of the auction affects how the Buy-It-Now price is set. We conclude that there is an inverse-U shape relationship between the Buy-It-Now price and the seller's payoff: up to a given threshold, the higher the Buy-It-Now price, the higher the payoff. Additionally, we observe that sellers tend to earn more in a closed-bid auction, while buyers earn more in an open-bid environment.

1. Introduction

Auction theory in recent years has become an even more important and talked about branch of economics, considering that the Sveriges Riksbank Prize in Economic Sciences was awarded to Paul R. Milgrom and Robert B. Wilson in 2020 for "improvements to auction theory and inventions of new auction formats" (The Nobel Prize, n.d.).

Paul R. Milgrom in his essay in the Advances in Economic Theory: Fifth World Congress (1987) stated that there are two main explanations behind the high demand for auctions. Firstly, this format leads to consistent and efficient outcomes - this is achieved by the underlying way an auction is set up. Each individual bids up to their personal perception of what the item is worth, not more. The second reason mentioned by Paul R. Milgrom is the opportunity the seller has in the relatively low bargaining power position they find themselves in. By executing the auction format, the seller selling the item gets the highest possible payoff by bargaining the item for the highest possible price, while having the buyer on the other side of the bargain still better off as they had purchased the item below their perceived intrinsic value of the item. These reasons make the auction format one of the more popular ways to sell an item based on basic utility theory.

Auction theory can and is applied every day not only in the traditionally thought of examples we may observe in the movies such as those unreachable expensive car and artwork auctions attended by elite collectors but, the most common environment is in the online format. The online format is quite the opposite of the previously mentioned collector's auction as its format allows for any individual with a working internet connection and some proof of funds to participate in the auction of their choice, making the experience almost universally attainable. eBay has been the pioneer in this form and remains the most popular platform where users can compete against each other to try and outbid for the item of their choice, reaching 159 million active buyers in the second quarter of 2021 (Statista, 2021).

Low-stakes online auctions of regular day-to-day items are not the only environment auction theory can be useful in as many of the world's most demanded resources are sold via auction format, for example, government tenders are organized to find the best fitting contractors for projects financed by the public sector. Stock exchanges also use differing auction formats to concentrate available liquidity as well as set opening and closing stock prices. According to the London Stock Exchange (2020), opening day, intra-day, and closing day auctions are introduced throughout the trading day in which instant execution of orders is paused, submitted buyer prices are aggregated, and the most appropriate price for the sale of the specific equity is selected.

Taking into account that not only has the auction floor been created more attainable for the average individual but also the stakes could not be higher for participants in certain auction environments as some of the world's largest markets rely on this format to sell financial instruments, government projects, and oil resources, deeper understanding of the fundamental theory and or practical techniques to win auctions or vice versa make them fairer could not be in more demand.

The core idea behind our thesis is to replicate an experiment previously conducted for a paper by Tim Grebe, Radosveta Ivanova-Stenzel, and Sabine Kroger (2021). The authors of the original paper were investigating a specific functionality present in most auctions – the Buy-It-Now feature. Auction participants can use this function to purchase the item outright without having to participate in the bidding process that we associate with a typical auction format. After conducting their experiment, the authors concluded that compared to an auction without the Buy-It-Now feature, an auction with the feature generates significantly higher revenue for the seller.

There is a plethora of research on how the fixed price functionality affects the seller's revenue and buyer's payoff generated through the auction. However, there is a lack of studies on how the specific type of auction impacts the way auction participants use the Buy-It-Now feature. Therefore, we believe there is a gap in the public literature that we could supplement by organizing a set of experiments at our university to investigate this relationship between the auction type and fixed price functionality.

The conclusions and practicalities taken from this research could help to understand how the type of auction impacts seller's revenue from the auction format and which auction type would be most appealing to sellers with regards to setting the Buy-It-Now price for the item. These conclusions can be applicable to the high-stakes auction environments where even a slight deviation in chosen strategy with regards to the Buy-It-Now price can have a multi-million-dollar impact on the underlying sale. However, practical takeaways from this research could just as likely be successfully used to increase the revenue of a regular auction seller participating in an online auction, trying to kickstart their career in e-commerce but is unsure on the exact type of auction that should be used for their situation.

As Peter Fredriksson stated shortly after the announcement of the 2020 noble prize laureates in Economic Sciences, Paul R. Milgrom and Robert B. Wilson first began their work with the fundamental auction theory and then "later used their results in practical applications" (The Noble Prize, n.d.). We chose to follow the same approach and began by first studying the theoretical basics behind auctions and later applying this knowledge in a practical manner by using it in a real-life experiment and afterward explaining the observed behavior and results by the aforementioned theory.

To replicate the experiment, we organized simulated auctions for university students to participate in - 6 simulated auction sessions with 12 participants per session (total number of participants reached 72). In each session there were 4 auctions going on at the same time, each having 1 seller and 2 buyers. Each auction lasted for a maximum of 5 minutes, after which the buyers and sellers switched to different groups and went on to do the auction simulation again. Per session, there were 6 of these simulated auction iterations.

This will be done using the principle of experimental economics which is a practice in which individuals are placed in an economic environment and their behavior observed (Shor, 2011). This lab experiment where participants are randomly allocated and placed in a close to lab environment with highly regulated and monitored circumstances allows to track the cause and effect of variables artificially introduced by us so we can observe how participants act.

To build upon the original paper and add novelty from our side - we checked how changing the type of auction affected how sellers set their Buy-It-Now price. Therefore, three out of the six auction sessions were held under a different auction format - sealed bid, meaning buyers did not know their competitor's bid and could only bid once. We expect there to be a significant difference between sessions with a different auction type as there has been previously conducted research which involved looking at different auction types. In this paper the researchers observed that participants took on different bidding strategies (Stenzel and Kroger, 2008) which we believe could lead to a significant impact also on the Buy-It-Now price. The purpose behind these simulations was to observe the relationship between Buy-It-Now prices set by the seller and the auction type. As a result, we chose to impose the following research question:

How changing the auction from an open to a sealed-bid type affects how sellers pre-set their Buy-It-Now prices?

2. Literature review

In order to answer our proposed research question, a substantial amount of research has to take place in the realm of the aforementioned economics branch – auction theory. Specifically, we will attempt to look at some theoretical works explaining the different terminology, concepts, and ideas that are behind our paper and on which we base our experimental section. Theoretical points like some of the intuitions into how auctions function, how their result may be influenced in favor of either party, the different types of auctions that exist and are currently in use, as well as some key characteristics and functions available in modern auctions. We will also look at previously conducted analyses on the topics concerning our sphere of research. For example, how different auction features affect the seller's payoff, how different auction types affect the overall outcome and result, as well as how a fixed price option will impact the buyer's choices and their gained utility.

2.1 Auction fundamentals

To analyze how buyers make their choices with regards to bidding and how sellers decide on what fixed price option they will feature on their auction we first need to understand how an auction works and what processes take place in the background. The most widely used auction models, according to P. Klemperer (1999) are those with asymmetric information – where the knowledge of the intrinsic value of the item is not the same for all auction participants. This is also the more realistic model, as in real life each auction bidder also has their own unique perceived value of the product they are bidding for, otherwise, all auctions would end after the first bid is placed and neither the seller nor the buyers would be better off as both have the same value perception of the item. This auction model is called the basic private-value model. However, there are instances where the actual value of the underlying item is the same for everyone but the information each bidder has is private and thus they may have different perceived values of the commodity's worth. This model is called the pure common-value model and as an example, both P. Klemperer (1999), and P. Milgrom and R. Weber (1982) had mentioned the most conventional oil-lease auction. Each participant values oil more or less the same, but someone may have advantageous information regarding the actual oil supply available under the specific plot of land, in comparison to other auction participants that may not have this private information. These individual private sources of information create a different perception of the value of the item and can decide the winner of the auction.

2.2 Open-bid auction type

Open-bid or English auction – (we might use both terms depending on which better suits the context) is a type of auction with "ascending bids" (Coppinginer, Smith, and Titus, 1980). Meaning that in an English auction buyers are competing with each other through a span of time and the buyer with the highest bid at the moment of the auction's end is the winner. The information about the bids is open in an open-bid auction - available to the participants so they can place their bids by adjusting bidding strategies in accordance with other bidders' strategies.

Even though calling English auctions simply open-bid might result in some confusion because there are other types of open bid auctions, for example, the Dutch auction which has an opposite mechanism to English (descending price) is also considered to be open (Riley, 1989). We will stick with this definition because the English auction is the only type of open auction that will appear further in our thesis.

2.3 Sealed-bid auction type

The sealed-bid auction, on the contrary, is a type of auction that does not freely distribute information about the bids. In one-stage sealed-bid auctions, there is only one round when the bidders place their bids simultaneously and the participant with the highest bid wins. However, Perry, Wolfstetter, and Zamir (2000) suggest another type of sealed-bid auction – a two-stage sealed-bid auction. In two-stage sealed-bid auctions, there are two rounds. In the first round, participants bet blindly like in the default sealed-bid auction. However, only the two participants with the highest bids survive the first round and move on to the next one. The bids of all the eliminated participants are revealed after the first round. In the second round, the remaining two bidders participate in another sealed-bid second-price auction, however, their bids are limited – buyers cannot set prices lower than those they made in the first round.

2.4 Risk aversion

According to Riley (1989), the introduction of risk aversion allows for a deeper understanding of bids in a first-price auction because buyers can only bid once and there is not one apparent dominant strategy (as it can be in second-price auctions) which is why they need to take more risks. The more risk-averse the buyer, the higher the price they are willing to pay, which will then decrease their own payoff and increase the seller's revenue. However, the author also states that if buyers are risk-neutral with the same object valuation and same beliefs about each other's valuation assumptions, the revenue of the seller will not be affected by a change from an English auction to a sealed bid auction and vice versa.

In addition, R. Ivanova-Stenzel and S. Kroger (2008) state that second-price auctions without a reserve price and English auctions with a fixed price option do not return the same revenue. Furthermore, risk aversion applies not only to how buyers bid against each other but also how sellers tend to set their Buy-It-Now prices for the items in the auctions. R. Ivanova-Stenzel and S. Kroger (2008) state that with the help of risk preference measures we can investigate if their risk preferences improve the fit of the model by comparing the actual buyout prices with those we predict under risk neutrality.

2.5 Auction design and specification

Beside the type of auction, there is a variety of specifications that could be used to set up an auction. In this paragraph, we will go through the main functions relevant for our research to determine what is their purpose and how they theoretically should affect revenue for sellers and payoff for buyers. The buyout or buy-it-now feature, being one of the main focus points of our research, will be dealt with separately.

To begin with, there are different features that determine payoff. In the previous chapter we already mentioned the second-price auction - it is an auction in which the buyer who submitted the highest price pays the second-highest price (Shor, 2011). This type of auction setting is usually applied to sealed bid auctions, however, with certain modifications to an English auction, for example, by adding a second-price functionality, a Japanese auction is created.

On the contrary, there is the first-price auction type in which the buyer who submitted the highest bid (Shor, 2011) wins the auction and must pay the price at the level he set his bid. This is the usual type of price setup used by online auctioning platforms which usually use open bid auctions; however, it can be also applied to sealed bid auctions.

Due to the difference in payoffs, buyers have different bidding strategies. As suggested by Shor (2011), for the first-price auctions buyers can set their prices below their true value. However, in auctions that utilize the second-price functionality buyers' dominant strategy is to set their true value from the first bid. If the buyer wins a second-price auction he will pay less than his true value, hence, increasing his payoff from the auction.

Another specification that we believe is important to mention is the expiry time or the expiry mechanism. The expiry mechanism is a setup that affects how the auction ends when the bidding stops. There are different types of this mechanism that can be used during auctions - "hard-close" or "with time extension" (Roth and Ockenfels, 2002). Hard-close auctions stop when the time of the auction finishes, while those with time extension extend the auction by *n* minutes if the bid arrives in the last *m* minutes of the auction.

Auctions with time extension do not allow for additional specific strategies to be used, however, auctions that have hard-close times allow for sniping. According to Roth and Ockenfels (2002), sniping is a strategy that allows buyers to bid at the last minutes of an auction when there are no other buyers participating and place a bid which is larger than the previous highest bid by a small margin and hence win the auction without giving the opposing bidders an opportunity to submit a higher bid.

However, last-minute bidding can be solved with proxy bids – an instrument that allows a buyer to set the maximum price they are willing to pay for the item. A proxy bid will then automatically raise the buyer's bid until this maximum price is reached (Shor, 2011). In this case, the last-minute bid strategy will not help the buyer win the auction since a proxy bid set by another buyer will automatically outbid last-minute buyers.

Another risk that is hidden in the last-minute bidding strategy is caused by technical problems. Roth and Ockenfels (2002) give two examples of how this might happen - firstly, the last-minute bidders might simply not get access to the auction due to problems with their internet. Secondly, last-minute bidders seek for an opportunity to be the definite winner in an auction they are participating in, however, due to their overly risk-seeking behavior they sometimes bid too late and lose out due to technical limitations of the auction platform itself - the platform may be unable to process and place the bid in time, making the last-minute bidder lose out in this situation.

In conclusion, the authors state that last-minute bidding becomes a viable strategy in hard close auctions, and empirical proof obtained during their research suggests that experienced bidders stick to this strategy more often than less experienced participants. Thus, the choice between a hard-close and a with-time extension auction can drastically impact the outcome of an auction.

2.6 Reserve price

Reserve price, according to Shor (2011), is the minimum bid allowed in the auction. According to Cai, Riley, and Ye (2007), sellers have an incentive to set their reserve prices at the level of the true value of the object as it tends to increase the buyers' perceived valuation of the item which has an effect on their bidding strategy. In their conclusions, the authors state that the reserve price increases with the number of buyers under certain conditions. Overall, a reserve price serves as a signal to the seller's actual perceived value of the item and can be used to interpret the seller's perspective. However, according to Hinz and Spann (2014), there are auctions in which the reserve price is not stated explicitly which results in buyers not having full information about the auction and they would have to bid higher than this unknown reserve price in order for their bid to count. In this case, buyers have another incentive – to bid closely or marginally above the reserve price

2.7 Buy-it-now

In their work J. Gallien and S. Gupta (2007) mention that when online auctions were the newly created alternative to conventional in-person auction houses, in the 1990s, there were two main issues with the concept:

- waiting time,
- price uncertainty.

In comparison to on-site auctions, the online alternatives could not conduct the auction in one day as bidders were not all attending the same room at the same time. Instead, the way it works with online auctions is that buyers browse the online auction platform for potential items they would like to bid on and make their choice over the course of multiple several days or weeks. For this reason, most of the auctions on the most popular online auction websites take place over a longer period of time – multiple days or even weeks, in order to give all potentially interested users the opportunity to take note of the auction and make their bid. This meant that online auctions on average would last 7 times longer than a regular in-person auction could. Another issue is the price uncertainty, which is closely connected to the prolonged waiting time. As the auction itself would last much longer than normal, the bidders would be left uncertain for a much longer period of time, wondering if their bid is high enough to acquire the item in question. These two concerns were addressed when the most popular online auction platforms introduced a fixed-price functionality.

Auctions widely differ depending on the price functionality offered to their buyers. Specifically, whether they include the possibility to also buy the item for a fixed price stated by the seller beforehand. This fixed-price functionality is often termed as the take-it-or-leave-it price or the Ultimatum price (Binmore, 1991), however, each online auction platform has given its own distinct name to this feature – eBay calling it the Buy-It-Now option, while Yahoo, another online e-commerce giant which is most popular in East Asia, especially, Japan, have named this the Buy-Now feature (Reynolds & Wooders, 2009).

These hybrid type auctions have gathered popularity in the most popular online auction platforms which offer both the possibility of bargaining for the selling price of the item and paying a fixed price if the customer so chooses. This lures in buyers with different preferences and utilities - both those looking to participate in a live auction, ready to fight to get the item for the best price possible yet still offers the option to purchase the item outright to buyers willing to pay a premium who wish to skip the back-and-forth experience. According to S. S. Reynolds and J. Wooders (2009), about 40% of eBay auctions offer the fixed price functionality, while for Yahoo that figure reaches an impressive 66%, proving that the feature is favored by a large portion of online auction platform users.

This popularity of the Buy-It-Now option can be first thought of as being quite illogical as it may be expected to result in underachieved revenue for the seller of the auction. This idea is caused by the perception that by introducing a fixed price at the beginning of the auction, the seller effectively creates a limit price, up to which the buyers would be willing to bid up to – the fixed price serving as a perceived intrinsic value ceiling for the product. However, many authors have indicated quite the opposite, that the introduction of a fixed price purchase option benefits the seller. For example, S. S. Reynolds and J. Wooders (2009) had observed that when buyers have a high-risk aversion the auctions tend to generate more revenue for the seller if the Buy-It-Now price is put in place. In the paper by T. Grebe, R. Ivanova-Stenzel, and S. Kroger (2021), which we are using as a base for our own experiment, the authors concluded that the presence of a Buy-It-Now price had a significant positive impact on sellers' revenue.

An interesting point that many authors also put a major focus on is the risk aversion preferences of the buyers. As already mentioned, S. S. Reynolds and J. Wooders (2009) concluded that specifically risk-averse buyers participating in the auction cause an increase in the seller's revenue from the fixed price feature. The authors reason that this could be due to the fact that risk-averse buyers are more afraid of losing out on the item in the course of the auction and therefore tend to buy at the high fixed take-it-or-leave-it price – which also includes a risk premium. The same observation is also made by S. S. Reynolds and J. Wooders (2009) that if sellers encounter risk-averse buyers, the anticipated profit is expected to increase. Additionally, the authors note that it is important to take into account the risk-aversion preferences of sellers as well, as they note that the highest profit is generated when sellers are risk-neutral, but buyers remain risk-averse.

There has been extensive research into how the Buy-It-Now system works and how it impacts the overall results of the auction. The previously mentioned paper by S. S. Reynolds and J. Wooders (2009) focuses on understanding how the risk preferences of sellers and buyers impact sellers' revenue in both eBay's Buy-It-Now auctions and Yahoo buy-now auctions. Their main conclusions are that participant risk preferences have a significant and lasting impact on the outcome of the auctions. Specifically, they emphasize that when buyers are risk-averse, fixed price functionalities raise seller's revenue on both platforms, however, the Yahoo buy-now functionality is preferred by sellers as it yields a higher increase in seller's revenue. The difference between the two platform functionalities is that under the eBay Buy-It-Now feature, buyers may purchase the item for a fixed price only before the starting bid is placed, while under the Yahoo buy-now rules, there is no such limitation and bidders can purchase the item at the fixed take-it-or-leave-it price any time they wish. From the bidders' perspective, when buyers have constant absolute risk aversion the two platforms' fixed price feature has the same payoff increase, if the bidders have decreasing absolute risk aversion the eBay Buy-It-Now feature is preferred, while if the buyers have increasing absolute risk aversion the Yahoo buy-now option is more preferred by the bidders.

Another paper that studied the difference in the effectiveness of the permanent fixed price option, as eBay offers to its users, and the temporary buy-now price seen on some of Yahoo auctions, is on the research done by J. Gallien and S. Gupta (2007). The authors had studied how a permanent fixed price option would affect the auction seller's revenue in comparison to a temporary price. After conducting their numerical experiments, they concluded that by introducing a permanent take-it-or-leave-it price, the expected revenue was higher than the non-permanent counterpart, but it also incentivized late bidding and thus also had a negative effect on the seller's payoff. They also, however, drew a more general conclusion that if a bidder is time-sensitive, the fixed price functionality can significantly increase the seller's revenue from the auction.

With regards to the impact of a fixed price option on the auction revenue, there are conflicting conclusions in previous research. In the previously referenced work by S. S. Reynolds and J. Wooders (2009), by J. Gallien and S. Gupta (2007), as well as by T. Grebe, R. Ivanova-Stenzel, and S. Kroger (2021), which we use for the base of our research, it has been concluded that the take-it-or-leave-it price inclusion has had a significant impact on seller's revenue. However, according to research done by S. Anderson, D. Friedman, G. Milam, and N. Singh (2008), there is no benefit to the seller in the use of a fixed price option if the buyers are deemed as risk-neutral. The authors explain this result by stating that the bidders of these auctions do not choose to purchase the product for the fixed price set by the seller and instead just enter the bidding stage when the seller tries to gain an advantage through the Buy-It-Now price – by making it too high and adding a premium on top of the widely accepted perceived value of the item. The buyers only choose the Buy-It-Now if the premium is insignificant or non-existent – thus there is no reason for the seller to even include the fixed price feature as the only point where the bidders will accept the fixed price is when it is more or less equal to the value the auction would reach anyway through a conventional bidding process.

Another important factor affecting the efficiency of a fixed price option is the auction type in which the feature is applied. The large majority of the previously mentioned papers covering the impact of including a Buy-It-Now price have used open-bid English auctions. However, there are also some papers that examine the impact of a fixed price feature in a sealed-bid auction environment, where the buyers submit their bids anonymously – each bidder has to make their decision without knowing what the competition had bid on the item. For example, in a paper by R. Ivanova-Stenzel and S. Kroger (2008), the authors examine the effect a take-it-or-leave-it price option has on the choice of auction bidders in a sealed-bid environment. The main conclusion drawn from the experiment was that most of the items were auctioned off during the sealed-bid auction, however, there was a significant number of instances where the buy-it-now price was accepted by the bidders. The authors explained these occurrences by stating that the fixed price set by the seller was either too low or the accepted price was too high.

There is, however, not a lot of research comparing the two auction types to understand if the Buy-It-Now price feature and its performance are dependent on the type of auction in question. Thus, we believe there is a gap in the research that we could fill by conducting our own experiments and comparing the fixed price option setting in two different environments – an open bid auction and a sealed bid auction.

3. Methodology and Data

3.1 Experiment process

For the methodology of our research, we decided to replicate the experiment by Grebe et al. (2021). This approach allows for the creation of a unique dataset as well as a possibility to determine a causal effect of the changed variable. As our research question suggests, we want to observe the causal effect of changing the auction type from a classic English auction to a sealed bid type which the controlled environment allows us to do as we can adjust the setup of the experiment according to our needs.

For the experiment, we invited 72 people to participate – Year 1 to Year 3 students from the Stockholm School of Economics in Riga, as well as some school alumni and exchange students. We asked them to register an account beforehand so they can participate in the auction sessions. 72 people were randomly assigned to one of the six sessions – 12 individuals per each one. In every session there were 8 buyers and 4 sellers; these 8 buyers were assigned to specific auctions based on a stratified matching scheme mentioned in the paper by Grebe, et al. (2021). In each session, there were 6 rounds (i.e., 6 auctions).

Sellers kept their roles through the whole session, while buyers are assigned either a priority buyer or regular buyer role. The seller's duty was to examine the item that is about to be auctioned off and give us their preferred Buy-It-Now price. After that, priority buyers could decide whether to buy the item for the fixed price set by the seller or submit their bid. Next, in the English auction, we let the bidding process start. Buyers had two minutes to bid on the given items after which we stopped the bidding process and proceeded to the next round. In our experiment, similarly, how it was done in the original paper, the participants were bidding to win economics books, however, as will be explained later, winners did not receive these items – instead they received a certain number of points that could be spent on gifts from our sponsors[1].

In a sealed bid auction, the first part is almost the same as the English auction – sellers give the preferred Buy-It-Now price and priority buyers have one minute to decide whether to accept the fixed price and purchase item for it or to participate in the bidding process later. After priority buyer's decision, if they do not exercise the Buy-It-Now price option, both priority and regular buyers are given 1 minute to decide what size bid they wish to submit. After one minute, both buyers submit their bids simultaneously, and the auction proceeds to the next round.

The reasons behind why we decided to proceed with a first price sealed-bid auction rather than a second price (or even a two-step sealed bid auction): firstly, participants already have a lot of instructions to follow at the same time. Making another set of special rules for their payoff will simply make them keep in their head another variable which may result in additional confusion during the experiment. The second reason why we chose the first-price auction was to avoid any additional technical difficulties during the realization of the second-price auction because of its absence in the functionality of the auction platform we used.

Overall, we had 72 participants - 3 sessions were conducted in an English auction environment, used as a control group, and 3 as treatment with a sealed bid auction. To control for population biases, we tried not to let any of the groups participating in the auctions overweight each other, for example, we on purpose tried not to propose experiment times

[1] We had contacted 37 consumer good companies in addition to our university's alumni network regarding potential cooperation. Out of those initial interactions we were able to establish beneficial partnerships with 8 companies where through providing a marketing service or simply through a donation we were supplied with different types of products to use as gifts to our experiment participants. The types of gift items spanned from oral hygiene products to chips, energy drinks and confectionary produce.

where it was difficult for Year 1 students to participate, making the session population more biased toward Year 2 and Year 3 students.

We calculated the payoffs for the sellers the following way - sellers get the highest bid as their payoff (whether it is a bid placed during the auctioning process or an accepted Buy-It-Now price). For buyers, however, only the buyer who won the auction (whether through buyout or bidding) gained a payoff. We calculated this payoff by subtracting the individually assigned private value from the price paid by the bidder for the item: Price paid – private value (PV).

Private value is a number assigned to each buyer which represents the intrinsic value of an item placed on the auction for the specific buyer. PV can differ between 1 and 50 and is assigned randomly – the list of participants was entered, and each individual was generated a random number between 1 and 50 using random value function in R Studio.

In addition, we followed the guidelines of the original paper and set the reserve price at the minimum possible level which allows bidders with any private values to participate in the experiment. Furthermore, our research is aimed at Buy-It-Now prices and not private values which makes it unreasonable to manipulate private values outside the guidelines of the original paper by Grebe et al (2021).

When getting a payoff, participants face an exchange rate of 1 auction EUR into 1 auction point. Participants can get real-world rewards supplied by our sponsors in exchange for auction points. This created a for-profit environment, similar to a real-life auction where participants are incentivized to win. The addition of an actual tangible payoff brings our auction simulation closer to a real-world setting.

During the experiment, participants cannot communicate with each other – when bidding they can only see the amount bid by the buyer, however, neither their name nor their personal information is displayed. The same applies to the seller - they can access the information about the bids placed by the participants but have no access to who the bidding user is. In case participants want to ask questions about the experiment process we let them do it in direct messages on Facebook's messenger platform in order not to disclose any personal information on who has asked the question and to keep the role of the participant private until the end of the auction.

Just like Grebe et al. we used the test for risk aversion by Holt and Laury (2002) to determine the risk preferences of the participants by sharing a survey consisting of 10 questions similar to the survey made by Holt and Laury (2002) in their study. A table that includes all the questions included in the risk aversion survey presented to experiment participants is available in appendix A – a table taken from Holt and Laury (2002) which was used as an inspiration and as a rule of thumb to determine risk preferences of sellers and buyers.

To replicate the experiment, we had to switch from the eBay auction platform (which was used in the original paper) to 32auctions as it allows us to implement the same functionalities as the eBay platform does. The switch was dictated by the technical difficulties we faced trying to use eBay – the website limited us to 3 running auctions per account (with 4 set up accounts on our side) while we needed at least twice that amount. 32auctions, however, allows us to set up auctions with a Buy-It-Now functionality and has the same auction expiry mechanism without having the account limitations that we encountered on eBay – this determined our switch to the new platform.

3.2 Data

In our research, we created our own unique dataset out of the data we received from the experiments we organized and the risk preference survey we distributed. During the experiment we collected the data on all the Buy-It-Now prices set by the sellers, all the bids made during the auction, the information whether the fixed price was accepted, information on all individual PV, payoffs, and information on which auctions the participants took part in the sessions.

From the risk preference survey, we have gathered the answers that the participants gave on different questions. Thus, we have some demographic characteristics of the participants as well as information on their risk preferences rated on the basis of the risk aversion test published in the paper by Holt and Laury (2002).

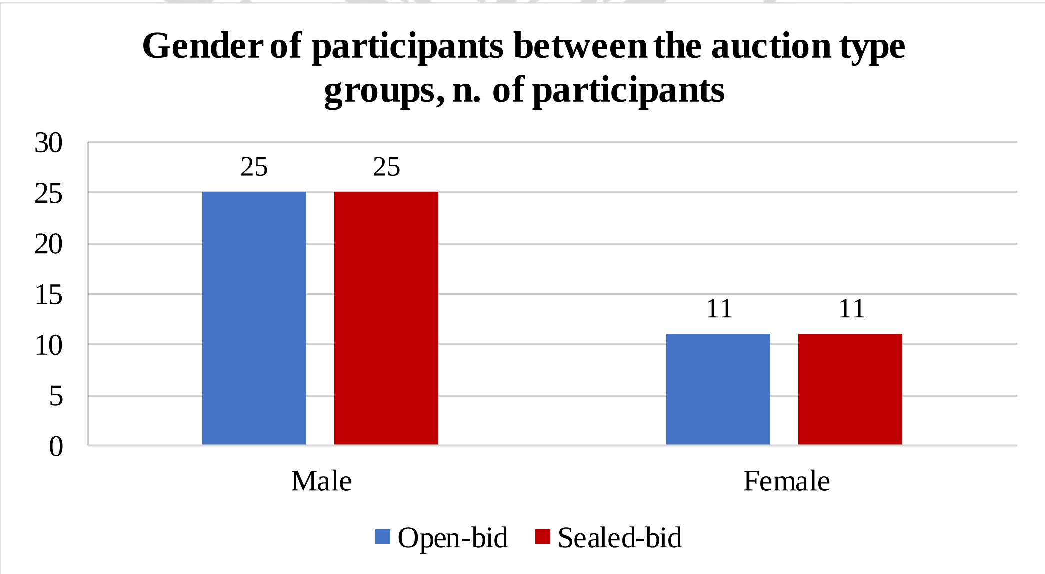
4. Analysis and Discussion

To start, it is first important to understand and analyze the characteristics of the data we have acquired - this can, for example, allow us to take into account any significant demographic biases our data may include which may skew the overall results of our experiment. Thus, we look at the demographic data we have available from our experiment – specifically, what kind of people attended and participated in our organized auctions, which we gathered through the risk aversion survey that was distributed to all experiment participants.

4.1 Demographic variables

The first aspect we look at is the gender distribution within our experiment control and treatment groups. As can be observed from Figure A1, the gender distribution between the two auction-type groups within the experiment is even. Meaning, 25 males and 11 females participated in the 3 control group experiment sessions conducted under the open-bid auction type, at the same time 25 males and 11 females also participated in the 3 treatment group experiment sessions conducted under the sealed-bid auction type. This means there is no difference between the control and treatment groups in terms of gender distribution. Thus, we can rule out any general skewness of results due to gender distribution when comparing the results between the control and treatment groups. It is important to take the gender distribution into account due to different conclusions based on the specific auction type – according to E. E. Rutstrom (1998) the gender of the auction participants has no impact on the underlying result and payoffs in open-bid. However, Y. Chen, P. Katuscak and E. Ozdenoren (2012) after conducting their experiment in a sealed-bid format concluded there was a significant difference observed between how males and females participated in the bidding of auctions, indicating that during first-price auctions women on average bid much higher than men.

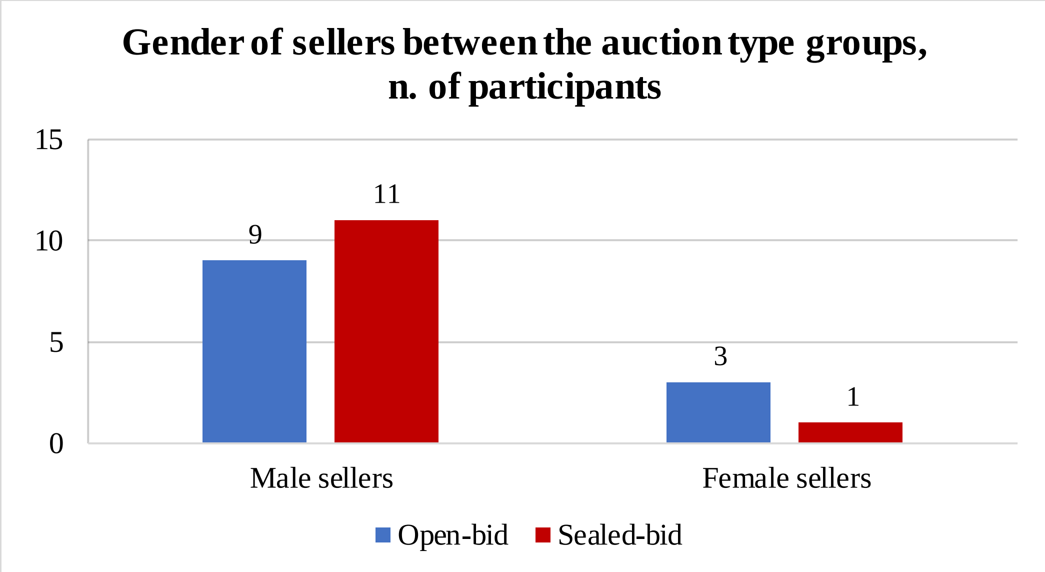
Figure A1. Gender of participants by auction type group.



Source: Authors created risk aversion survey.

Another important factor to look at is the gender distribution within the roles participants took in the experiment, as the type of role a participant was randomly assigned could have a significant effect on the underlying result of the experiment.

Figure A2. Gender of sellers by auction type group.

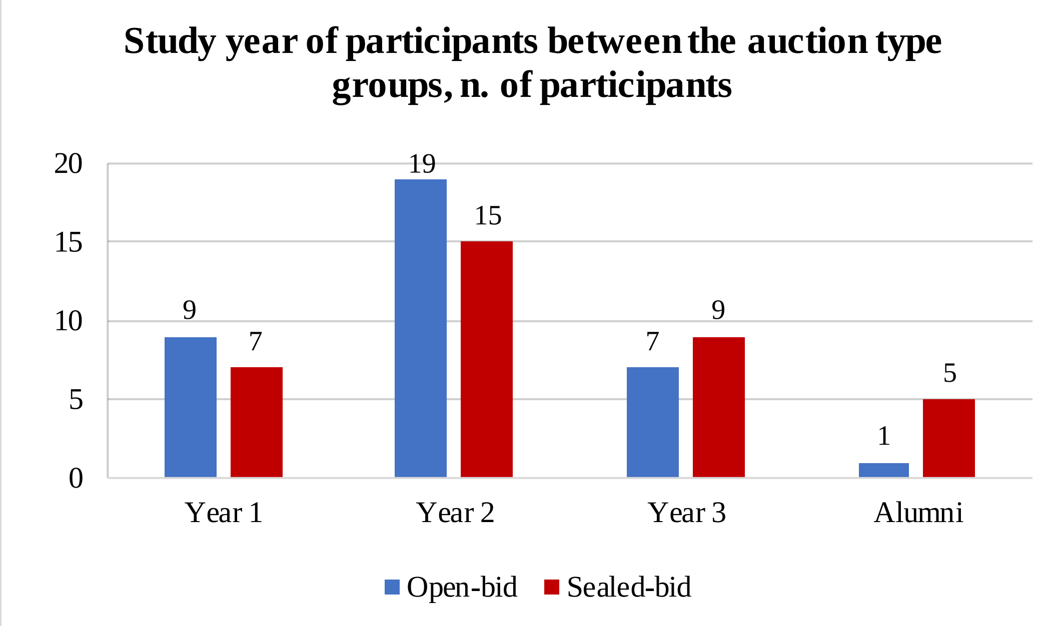


Source: Authors created risk aversion survey.

As observed in Figure A2, the gender distribution of participants who were randomly assigned the role of being the seller is not equal between the control and treatment groups, however, the deviation is slight. Meaning, 9 male sellers and 3 female sellers participated in the 3 open-bid auction sessions, while 11 male and 1 female seller participated in the sealed-bid auction sessions. The large majority of the sellers in both groups is still male, however, there is a slight deviation that has to be taken into account when analyzing a role-dependent research question.

The second important demographic variable we can analyze is the year of studies since all of our experiment participants are or were students at the Stockholm School of Economics in Riga. The study year distribution can indicate the general experience level of the participant as higher year students have had the chance to take part in more of the school's curriculum as well as had more opportunities to participate in other work-related environments.

Figure A3. Study year of participants by auction type group.



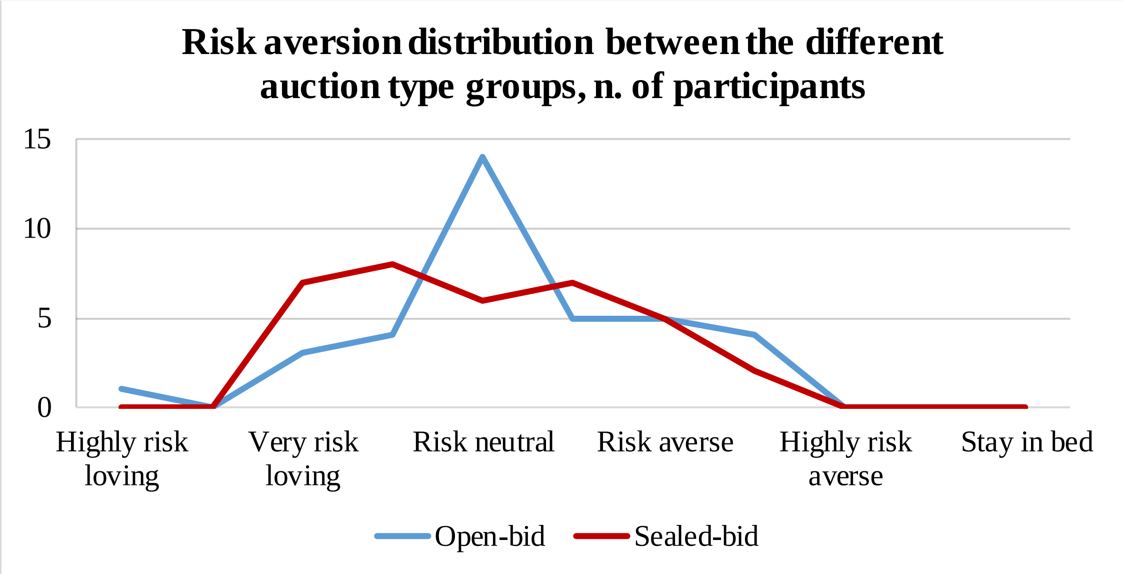
Source: Authors created risk aversion survey.

From Figure A3, we can note the current study year of the experiment participants between the control and treatment groups. In general, the majority of the participating students were in their 2nd study year – 34 students in total, while the number of Year 1 and Year 3 students remained equal – 16 students per each. The smallest group by the number of participants consisted of alumni – 6 university graduates in total.

We can conclude that across the 3 study years the number of participants in open-bid and sealed-bid auctions differ but only slightly – there are more Year 1 and Year 2 participants in open-bid auctions, while there are slightly more Year 3 participants in sealed-bid auctions. Alumni deviate quite a bit more, as 5 out of the 6 graduates participated in the sealed-bid auctions, compared to only 1 in the open-bid group. Apart from the alumni, the deviations are quite small, however, there is a general trend that more senior students had participated in the sealed-bid auctions which we would have to take into account in further analysis.

Next, we have looked at the general risk aversion distribution of the experiment participants between the control and treatment groups. This measurement was collected by having each participant fill out the previously mentioned risk aversion survey.

Figure A4. Risk aversion distribution by auction groups.



Source: Authors created risk aversion survey.

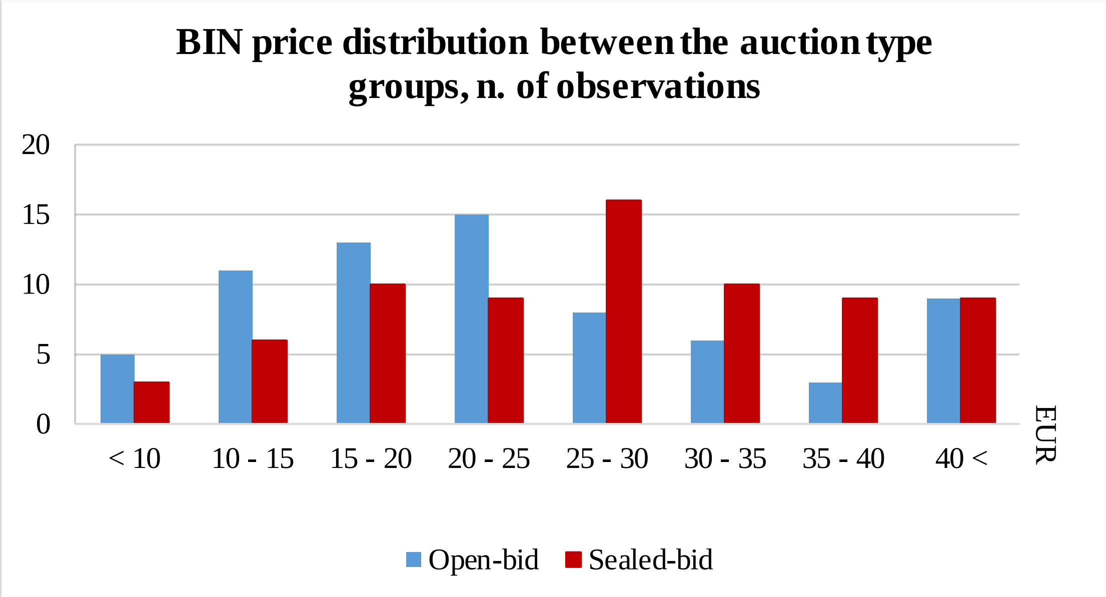
In Figure A4 the risk aversion distribution of the experiment participants can be observed. The majority of the experiment participants were risk-neutral, while the spread between the different types of auctions had differed – the graph depicts a clear peak in risk-neutral participants for the control group, while the treatment group graph is more evenly distributed and slightly skewed toward the risk-loving side of the spectrum.

Thus, we can conclude that open-bid auctions had the large majority of their participants being rather risk-neutral, while sealed-bid auction participants were slightly more risk-loving. This slight difference in risk aversion distribution amongst the participants of the control and treatment groups will be taken into account during further analysis.

4.2 Seller aspect

As the demographic characteristics of experiment participants have been reviewed, we can move on to answering the main research question of the paper - how changing the auction from an open to a sealed-bid type affects how sellers pre-set their Buy-It-Now prices? Firstly, we plotted a histogram to see the distribution of Buy-It-Now prices set by the sellers in the two different auction type groups to see if any relationship could be observed.

Figure B1. Buy-It-Now price distribution by auction type.



Source: Authors created a dataset based on the authors' organized experiment.

From Figure B1, we can observe that overall, the BIN price distribution somewhat evenly distributed on both ends of the spectrum with a peak in the median values for both the control and the treatment groups, staying within the previously stated margins of the BIN price (1 – 50 euros). However, it is evident that the distribution of the open-bid group is slightly skewed to the left, while the sealed-bid group's distribution is skewed to the right. Meaning, the sellers of the open-bid auctions have on average set smaller Buy-It-Now prices for the same auctions than the sellers of the sealed-bid auction. This visual representation suggests a correlation between the type of auction and the BIN prices set by sellers. This, however, does not necessarily indicate causality between the auction type and Buy-It-Now prices, which is our research question.

To answer the question whether the auction type has a statistically significant effect on the BIN prices, we have aggregated the data acquired from the experiment into one dataset and ran a simple linear regression where the auction type explains the Buy-It-Now price set by the seller. The result of this regression can be observed in Table A1.

Table A1. Auction type regressed on the BIN prices set by sellers.

Linear regression of auction type explaining Buy-It-Now price (R^2 = 0.013; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	26.666	1.285	20.747	<2e-16
Auction.type	-2.476	1.818	-1.362	0.175

Note: From authors ran regressions based on authors' created dataset.

As a result, the coefficient indicating the impact a change in the auction type has on the BIN prices set by the sellers is -2.48 with a p-value of 0.175, meaning the coefficient is statistically insignificant at the widely accepted 10%, 5%, and 1% significance levels (after conducting the Breusch-Pagan Test for Heteroscedasticity which can be seen in appendix B, table B20, the p-value is 0.32, thus the regression is homoscedastic – unbiased and efficient). Thus, we cannot rule out the fact that there may be no impact and there may not be a causal effect according to this regression. However, taking into account that the coefficient is quite large and the p-value is fairly low and close to being statistically significant, we cannot rule out the possibility that with more experiment sessions this effect could be statistically significant and the culprit is the low number of observations. Perhaps this is a good basis for further research.

Another important point is looking back at the visual representation in figure B1 - there is a noticeable difference between the BIN prices set by sellers under open-bid and sealed-bid auctions. However, our regression proves that the auction type does not affect the BIN prices. Thus, we may conclude that there are some other omitted variables dictating this difference and further research could be done on the topic to pinpoint these omitted effects and estimate them.

However, there are other potential variables that have a causal effect on the BIN price set by the seller that have been omitted from this simple linear regression. Therefore, we control for different demographic variables by adding them to the regression in order to see if there was any left-out effect. The first of the demographic variables we added was the coefficient for gender. Even though we previously reviewed the demographic characteristics of our data and concluded that there was no difference in gender distribution between the control and treatment auction type groups, we noted that there is a difference if we look at the gender distribution within the roles of the auction groups. As this research question involves looking only at seller data, this is the case where role gender distribution may be applicable. We also controlled for the study year of the seller and their risk aversion. We ran a simple linear regression where the BIN price set by the seller is now explained not only by the auction type but also by the gender of the seller, year of studies, and risk aversion (Table A2).

Table A2. Auction type, gender, year of studies, and risk aversion of sellers regressed on the BIN prices set by sellers.

Linear regression of auction type explaining Buy-It-Now price + controls (R^2 = 0.046; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	30.9653	4.4668	6.932	1.42E-10
Auction.type	-2.9611	1.9441	-1.523	0.13
Gender.coefficient	-5.1947	2.4913	-2.085	0.039
Year.coefficient	0.477	1.0767	0.443	0.658
Risk.aversion	-0.2427	0.5177	-0.469	0.64

Note: From authors ran regressions based on authors' created dataset.

The coefficient explaining the impact of gender on BIN price is approximately -5.19 with a p-value of 0.0389 (under the widely accepted 5% significance level). This means, we can state with a 5% significance level that the gender of the seller has an impact on the Buy-It-Now price the sellers set – the average BIN price set by a male was approximately 5.18 euros lower than the prices set by female sellers. The coefficients next to the year and risk variables were statistically insignificant, thus we conclude that they have no observable effect on the BIN price. Also, the coefficient next to auction type and its p-value had remained largely the same after controlling for the demographic variables so we can conclude it to be a fairly stable result. Additionally, we wanted to see if any of the control variables had an impact on how auction type explained the BIN price set by the seller but all of the coefficients were insignificant, thus, no impact was observed (see appendix B, Table B1, and B2).

On top of the analysis of the auction type impact on the Buy-It-Now prices set by the seller, we also decided to analyze if the BIN price set by the seller had an impact on the seller's payoff. This is a valid point to analyze because the authors of the original paper we were inspired by to conduct this experiment concluded in their research that the presence of a Buy-It-Now option does result in the increase of the seller's revenue. Thus, we ran a simple linear regression explaining the payoff of the seller by the Buy-It-Now price the seller put for the item. The result of this regression can be viewed in Table A3.

Table A3. Buy-It-Now price set by seller regressed on the payoff of sellers.

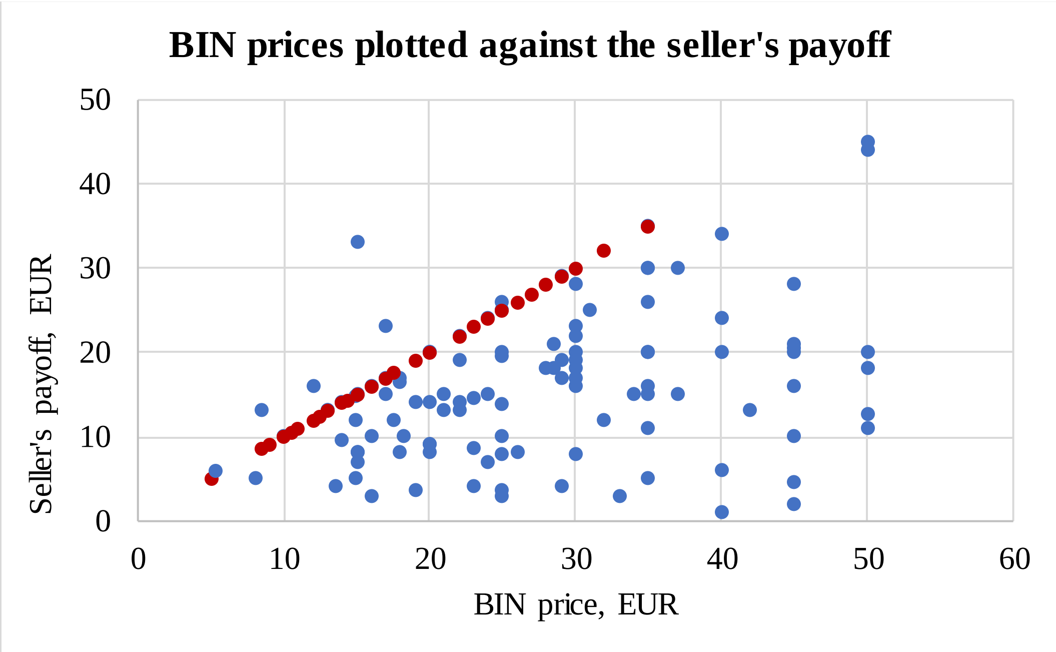
Linear regression of Buy-It-Now prices explaining seller's payoff (R^2 = 0.131; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	9.14421	1.7056	5.361	3.35E-07
BIN.price	0.28184	0.06146	4.586	9.98E-06

Note: From authors ran regressions based on authors' created dataset.

As a result, the coefficient explaining how the BIN price impacts the seller's payoff was positive but quite small. Thus, we can conclude that the higher the Buy-It-Now price set by the seller, the higher their payoff (the Breusch Pagan test showed a very low p-value, thus there is a sign of heteroscedasticity – while the OLS estimator is inefficient, the results are still unbiased). This is in line with our literature review as in the papers by S. S. Reynolds and J. Wooders (2009), by J. Gallien and S. Gupta (2007), as well as by T. Grebe, R. Ivanova-Stenzel, and S. Kroger (2021) they came to the same conclusion that the BIN price had a positive effect on the payoff of the seller. We, however, had a suspicion that this may not entirely be true as the higher the Buy-It-Now price set by the seller the less likely the buyer will have the necessary private value to be able to afford and pay the Buy-It-Now price and may instead opt to place a bid. This meant there may be a non-linear relationship in place as the impact may be positive up to a certain point before the BIN price becomes too expensive for the average buyer.

To see if our suspicions were correct, we plotted the BIN price observations on a graph which can be seen in Figure C1, to see what BIN price more often led to a higher payoff and if a non-linear relationship could be observed.

Figure C1. BIN prices plotted against the seller's payoff, EUR.



Source: Author created graph based on the authors' created dataset.

As can be seen on the graph, the observations colored in red are the ones that equaled the Buy-It-Now price set by the seller, meaning, the priority buyer decided to purchase the item at the BIN price instead of placing their bid and starting an auction. It can be observed that there are no observations where buyers paid the full BIN price above the 35 euro price mark. This coincides with our hypothesis that the relationship between the BIN price set by the seller and their payoff is most likely not linear. We, therefore, decided to add a squared variable of the BIN price into the regression in order to make it a non-linear relationship, the result of which can be seen in Table A4.

Table A4. BIN price and BIN price squared regressed on the payoff of sellers.

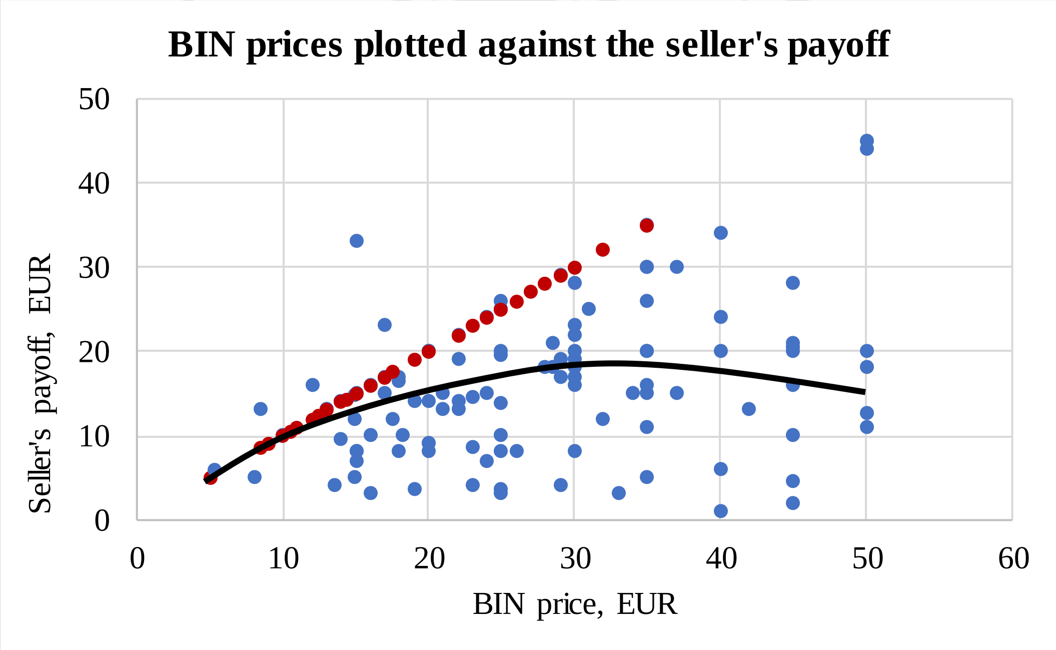
Non-linear regression of Buy-It-Now prices explaining seller's payoff (R^2 = 0.155; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	2.727691	3.668721	0.743	0.458
BIN.price	0.823837	0.281777	2.924	0.004
bin_squared	-0.009621	0.004884	-1.97	0.051

Note: From authors ran regressions based on authors' created dataset.

As a result, the coefficient explaining how the squared value of the BIN price impacts the seller's payoff is also statistically significant at the 10% confidence level, meaning our hypothesis of a non-linear relationship is also confirmed by the regression. The coefficient in front of the squared value has a negative sign, meaning that at one point the effect turns negative, suggesting a concave parabolic relationship between the BIN price and the seller's payoff. From this, we can conclude that there is an optimal Buy-It-Now price a seller can set that on average will lead to the highest possible payoff located at the peak of this concave parabola.

If we plot the non-linear regression line on the previously shown graph with all observations, we can see the approximate maximum seller's payoff achievable. The result can be viewed in Figure C2.

Figure C2. BIN prices plotted against the seller's payoff + regression line, EUR.



Source: Author created graph based on the authors' created dataset.

The highest point of the regression line is around the 34 EUR Buy-It-Now price – meaning that for sellers to maximize their average payoff, the best practice is to set the Buy-It-Now price in the range between 30 and 35. This will be a high enough price where the seller would earn a significant payoff but without discouraging away most of the buyers.

As in previous instances, we added certain demographic variables to check if the results of the initial regression were robust. The result of this regression with control variables can be observed in Table A5.

Table A5. BIN price, BIN price squared, gender, year, risk aversion of the seller regressed on the payoff of sellers.

Non-linear regression of Buy-It-Now prices explaining seller's payoff + controls (R^2 = 0.178; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	4.068617	4.776202	0.852	0.396
BIN.price	0.842427	0.282686	2.98	0.003
bin_squared	-0.009702	0.004893	-1.983	0.049
Gender.coefficient	1.190209	1.794737	0.663	0.508
Year.coefficient	-1.360117	0.770742	-1.765	0.08
Risk.aversion	0.183742	0.374823	0.49	0.625

Note: From authors ran regressions based on authors' created dataset.

The coefficients next to BIN price and BIN squared remain largely the same and statistically significant, thus, we can deduce that this result is stable. However, what we can also observe is that the control for the study year is also statistically significant at the significance level of 10%. Meaning, the higher the study experience of the seller, the lower Buy-It-Now prices they set on average. This could be explained by more conservative behavior from older and more experienced participants, however, we lack the necessary data and information to make such a case, thus, this could be an avenue to be explored outside the scope of this research. We also introduced the control variables and auction type as interactions, to see if the effect was based on the auction type used in the session (results can be viewed in appendix B, Table B3, B4, and B5) but no interesting results were found.

Following the explanation of how sellers' payoffs are impacted by the choice of the Buy-It-Now prices, we decided to further explore how sellers set those prices – specifically, how those choices have been made over the progression of the experiment. The reason behind this analysis was to see if there was any learning effect present, where sellers would take the experience of previous rounds into consideration in choosing to set their BIN price in further rounds. For this, we modeled a regression where the BIN price is a dependent variable and the round number is independent which explains the Buy-It-Now price. The results of this regression can be found in Table A6.

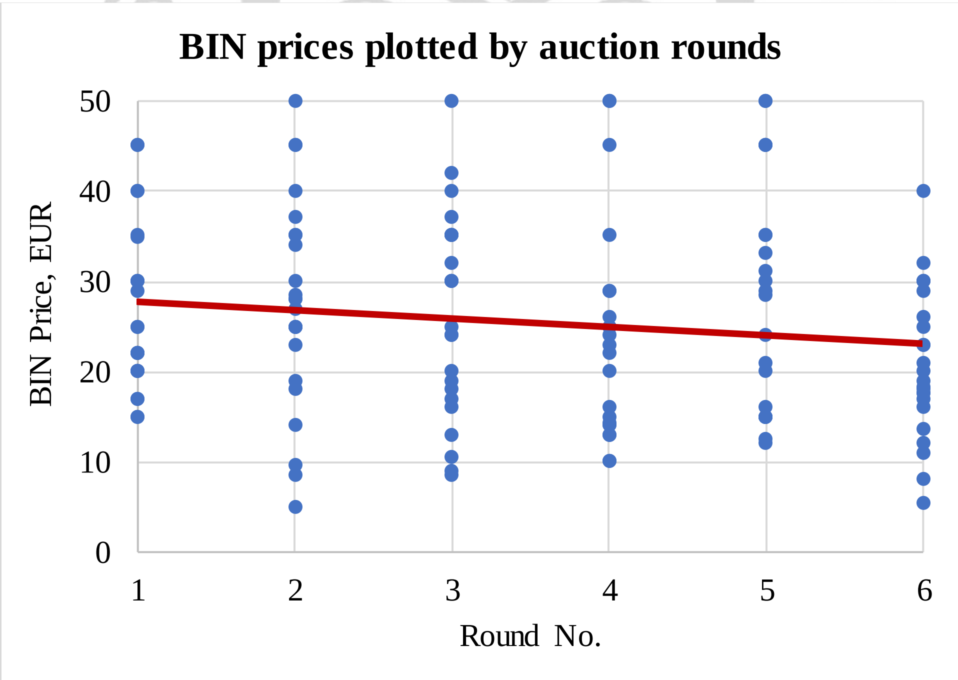
Table A6. The round of the experiment regressed on the BIN price set by the seller.

Linear regression of Round number explaining Buy-It-Now prices (R^2 = 0.022; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	28.6796	2.0638	13.897	<2e-16
Round	-0.929	0.5299	-1.753	0.082

Note: From authors ran regressions based on authors' created dataset.

According to the results visible in Table A6, we can conclude that the coefficient explaining the impact of the round variable is statistically significant at the 10% confidence level meaning that the sellers are indeed collectively learning through the auction and making a tendency to lower their BIN price in later rounds (the p-value of the Breusch Pagan test is 0.819, thus the result is homoscedastic – unbiased and OLS estimator remains efficient). The data was also plotted on a graph to visualize the tendency which can be seen in Figure D1.

Figure D1. BIN prices plotted against the auction rounds.



Source: Author created graph based on the authors' created dataset.

We assume that sellers may tend to on average lower their BIN price in the last rounds in order to persuade the buyers to purchase the items at the Buy-It-Now price. Sellers may initially set the BIN prices too high, observe that items are not being bought straight away, and choose to lower them later on. This is also confirmed by Figure D1 – if we compare the first and last round, initially almost all BIN prices are above the 20-euro mark but in the last round the large majority of the BIN prices are below the 20-euro threshold.

We also perform a similar analysis to the previous research questions where we added different control variables to the model. The result of the control can be viewed in appendix B, table B6. The only control that ends up statistically significant is the control for gender. We decided to further explore the effect of gender on learning to see if the learning outcome for different genders is different. For this, we supplemented the current model with an interaction between the seller's gender and the round number, as well as between the seller's study year and round number. As can be seen in appendix B, table B7, and table B8, the interaction term, however, makes all variables statistically insignificant at all widely acceptable confidence intervals (even though p-values are not very large). Taking a look at the correlation between seller's gender and round variables, we observe that there is no correlation between them which is rather obvious since the seller's role was unchanged during the whole auction experiment session (the result of the correlation can be seen in appendix B, table B9). Overall, we can conclude that as the auction goes from round to round the sellers are learning upon their previous experience and adjusting their BIN prices to be lower in the later rounds – with each new round the average Buy-It-Now price set by the sellers decreases by 0.9290 euros.

From our literature review, we mentioned that in an experiment by Ivanova-Stenzel. & Kroger (2008) the authors examined the impact of the Buy-It-Now functionality also in the sealed-bid auction type. Therefore, we decided to take a look if the two different auction types had an impact on the seller's payoff to see if there is some benefit for them to participate in a specific type of auction. For this we modeled another regression with the type of auction explaining the payoff of sellers – the result can be observed in Table A7.

Table A7. Auction type regressed on the seller's payoff.

Linear regression of Auction type explaining seller's payoff (R^2 = 0.049; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	18.2339	0.9971	18.286	<2e-16
Auction.type	-3.772	1.4052	-2.684	0.008

Note: From authors ran regressions based on authors' created dataset.

The coefficient explaining the impact of different auction types on the seller payoff equals -3.77 and is statistically significant at a 1% confidence interval (after the Breusch

Pagan test we conclude that the p-value is 0.46, indicating homoscedasticity – an unbiased result and an efficient OLS estimator). Meaning, we can state that on average seller's payoff increases by 3.77 euros if the auction type is changed from open to sealed bid, which is also backed by Ivanova-Stenzel. & Kroger (2008) research on sealed-bid auctions. Similar to all the previous models we also applied control variables, the result of which can be seen in appendix B, table B10. In this model, the only significant control variable is the study year variable – indicating that the more senior the seller the smaller the payoff. However, as we had previously discussed, additional research would be necessary to explain such a statistical significance. We also add interaction variables between the Type of auction and Gender as well as Study year (the result can be seen in Appendix B, Tables B11, B12) but there is no additionally significant result.

4.3 Buyer aspect

From now on we wanted to change focus from the seller role to buyer role to examine their side of the experiment and how their actions, as well as the auction circumstances, impact their result. Firstly, we want to see how buyers benefit from different types of auctions. For this, we replicate the previous regression model but replace the seller's payoff with the buyer's payoff. The result of this regression can be viewed in Table A8.

Table A8. Auction type regressed on the buyer's payoff.

Linear regression of Auction type explaining buyer's payoff (R^2 = 0.02; No. of observations = 284)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	4.9648	0.8611	5.766	2.1E-08
Auction.type	2.8934	1.2178	2.376	0.018

Note: From authors ran regressions based on authors' created dataset.

In the basic linear regression with auction type explaining buyer's payoff the coefficient before auction type is 2.894 and it is statistically significant at the 5% confidence level, meaning buyers earn on average by 2.89 euros more in an open-bid auction (after the Breusch Pagan test with a p-value of 0.034 we conclude that heteroscedasticity may be present, meaning the OLS estimator is potentially not efficient but the result is still unbiased). Similar to other models, we also added control variables and interactions to the model. However, according to appendix B, table B13, B14, and B15, this did not result in statistically significant coefficients for any of the control variables. As a result, from the buyer's point of view, it is more fruitful to participate in open-bid auctions where they can base their starting bid on the opponent's input, not having to blindly set their bids close to their private value to win the auction.

Lastly, we also chose to examine if risk aversion has any impact on the way buyers set their bids. To study this point deeper, we decided to regress buyers' hypothetical payoff if their highest bid was accepted on their risk aversion metric as, according to Riley (1989), it allows for a better explanation and understanding of bid placement. However, as can be seen in the appendix B tables B16, B17, B18, and B19, the model did not return statistically significant results, and adding control variables as well as interactions did not have any effect on the bidding strategy either, apart from in the case of adding study year as an interaction. In this case, most variables suddenly become significant. However, due to the fact that as soon as we remove the interaction, the variables become very much insignificant, we believe that this result is very unstable and most likely an error. Meaning, through the analysis of our own dataset we could not determine that buyers' bidding strategy was significantly determined by their measured risk aversion.

5. Limitations

The main limitations of our paper are in our methodology and experiment process. First of all, due to coronavirus restrictions, we had to organize our experiment in the online format while the authors of the original paper conducted their experiment on-site. This means that the environments differ between the original experiment and ours, thus, any deviation in results could stem from this difference in format. Also, we theoretically would not be to control the environments of our participants, as well as the original authors, could in an on-site format. For example, we could not make sure that no communication is going on between the participants which could impact the end result of the experiment.

Secondly, even though we increased the sample of the original paper from 60 to 72, we suspect that one of our regressions shows an insignificant result due to there being not enough observations. 72 participants is higher than the original paper but still fairly low. However, organizing and managing an experiment like ours with this many participants was quite a challenge for two organizers and our limited resources, thus, increasing the sample size even slightly would be costly and potentially hinder the quality of the acquired results. In order to tackle this issue, this experiment would have to be tackled in a different environment with more participants.

Lastly, we have to recognize that our experiment was conducted with fairly homogeneous participants – students studying Economics in SSE Riga, in the age group of

18-22. This allows us to control for any significant effects stemming from age or experience differences among participants but at the same time makes our result quite unique to its participant pool. When applying the conclusions to a different environment with random participants the results may not be the same due to this point and further research with such a random sample would be necessary to confirm or deny our conclusions. However, in the scope of this research, we followed the same methodology as the original paper by T. Grebe, R. Ivanova-Stenzel, and S. Kroger (2021) in which the authors mostly also had business and economics students as participants.

Lastly, even though we mentioned the last-minute bidding strategy in our literature review, we could not check for it as the platform we used to host the auctions did not support this. However, we had an experience with last minutes bids in two sessions. Some participants had a strategy to wait until the last moments of the round to place their bid – some of them managed to do it in time, while some placed their bids after the timer ran out. In the latter case, we removed the bids as they should not count.

Overall, we did not check for the last-minute bidding strategy in our analysis as our dataset was not suitable to catch any meaningful results. However, this is an important point that could be tackled in a separate experiment where the format of the platform would be adjusted to account for this strategy.

6. Conclusions

In summary, we can draw certain statements and conclusions from our research that can be used in further real-life scenarios to improve bidding or selling strategy or potentially adjust the auction environment itself.

Firstly, we did not find indisputable evidence that the BIN price set by the sellers is in part determined by the type of the auction. However, given the high coefficient and the low enough p-value, we cannot rule out that given a higher number of observations, this effect could be found as statistically significant. Meaning, we cannot clearly state that the auction type impacts the way sellers set their prices and, on that base, their further strategy. However, it could be a good basis for further research as the p-value was quite low and the coefficient high enough to state that it is plausible that in an environment with more observations this effect could be observed as statistically significant.

Secondly, in the scope of our research, we observed that the BIN price does seem to be impacted by the gender of the seller. We can determine that on average BIN price is set by 5.18 EUR lower for male sellers compared to female sellers. This could be partly explained by the fact that through random role distribution we happened to have 20 male sellers as opposed to 4 female sellers. Due to this significant difference in gender distribution of sellers, the effect could be falsely recognized. To further comment on this observation, we would need to equalize the gender distribution amongst sellers but that would require organizing additional separate auctions sessions. However, the impact of gender on auction payoffs was not the focus of our research and could be tackled in further research.

Thirdly, the BIN price set by the seller was observed to have a non-linear impact on the seller's payoff – up to a certain BIN price threshold, the impact is positive (the higher the BIN price, the higher the payoff) and turns negative after this threshold. In our experiment, we concluded that this threshold is in the 30-35 EUR range. Thus, in order to maximize sellers' profits, sellers would need to set their BIN price in the range between 30-35 EUR. This could be explained by the fact that up to a certain point buyers on average agree to pay the BIN price set by the seller and thus the effect is positive (the higher the accepted BIN price, the higher the payoff for the seller). However, once a certain common-sense threshold is reached, buyers on average decide that the BIN price is too expensive and decide to reject it and place their bid.

Additionally, we observed a certain learning effect where sellers tend to on average lower their BIN prices in consecutive rounds. Sellers may initially set the BIN prices too high, observe that items are not being bought through the BIN price and choose to lower them later on in order to make the choice more favorable.

Finally, we observed significant evidence that depending on the role you hold in an auction, you will favor a specific auction type. From our research that on average seller's payoff increases by 3.77 euros if the auction type is changed from open to sealed bid. Vice versa, buyers earn on average 2.89 euros more in an open-bid auction. This means that sellers earn more in a sealed-bid auction, while buyers earn more in an open-bid environment. This can be used by sellers when they decide what type of auction, they wish to use to sell their items – choosing sealed-bid auctions where possible. Similarly, buyers should favor participating in auctions that are open bid in order to maximize their chances of earning a higher payoff.

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9. Appendices

Appendix A. Risk-Aversion Classification Based on Lottery Choices

Figure 1. Risk aversion classification chart.

Number of safe choices	Range of relative risk aversion for $U(x) = x^{1-r}/(1-r)$	Risk preference classification	Proportion of choices: Low real[a]	20x hypothetical	20x real
0–1	$r < -0.95$	highly risk loving	0.01	0.03	0.01
2	$-0.95 < r < -0.49$	very risk loving	0.01	0.04	0.01
3	$-0.49 < r < -0.15$	risk loving	0.06	0.08	0.04
4	$-0.15 < r < 0.15$	risk neutral	0.26	0.29	0.13
5	$0.15 < r < 0.41$	slightly risk averse	0.26	0.16	0.19
6	$0.41 < r < 0.68$	risk averse	0.23	0.25	0.23
7	$0.68 < r < 0.97$	very risk averse	0.13	0.09	0.22
8	$0.97 < r < 1.37$	highly risk averse	0.03	0.03	0.11
9–10	$1.37 < r$	stay in bed	0.01	0.03	0.06

Note: From *Risk aversion and incentive effects* (92(5), p. 1649), by Holt, C. A., & Laury, S. K., 2002, American economic review.

Appendix B. Results of regressions used in the analysis of variables.

Table B1. Auction type, study year, risk aversion regressed on the BIN prices set by sellers and gender as interaction.

Linear regression of auction type explaining Buy-It-Now price + controls with interaction (R^2 = 0.049; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	34.5962	6.9661	4.966	1.98E-06
Auction.type	-6.5455	5.6183	-1.165	0.246
Gender.coefficient	-8.2703	5.165	-1.601	0.112
Year.coefficient	0.4259	1.0814	0.394	0.694
Risk.aversion	-0.4344	0.5904	-0.736	0.463
Auction.type:Gender.coefficient	4.259	6.2617	0.68	0.498

Note: From authors' ran regressions based on authors' created dataset.

Table B2. Auction type, gender, risk aversion regressed on the BIN prices set by sellers and year as interaction.

Linear regression of auction type explaining Buy-It-Now price + controls with interaction (R^2 = 0.046; No. of observations = 144)

Variable	Coefficient	Std error	T-value	P-value
(Intercept)	30.231	4.9384	6.122	9.05E-09
Auction.type	-0.9267	6.0728	-0.153	0.879
Year.coefficient	0.7918	1.3994	0.566	0.572
Gender.coefficient	-5.1797	2.4995	-2.072	0.04
Risk.aversion	-0.2841	0.5324	-0.534	0.595
Auction.type:Year.coefficient	-0.8013	2.2651	-0.354	0.724

Note: From authors' ran regressions based on authors' created dataset.

Table B3. BIN price, BIN price squared, study year, risk aversion regressed on the seller's payoff and gender as interaction.

Non-linear regression of Buy-It-Now prices explaining seller's payoff + controls and interactions (R^2 = 0.219; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	3.77759	10.34487	0.365	0.716
BIN.price	1.30994	0.72097	1.817	0.072
bin_squared	-0.01901	0.01222	-1.556	0.122
Gender.coefficient	8.04308	10.73465	0.749	0.455
Year.coefficient	-1.78814	0.78219	-2.286	0.024
Auction.type	-3.477	1.4146	-2.458	0.015
BIN.price:Gender.coefficient	-0.72041	0.77928	-0.924	0.357
bin_squared:Gender.coefficient	0.01349	0.01327	1.017	0.311

Note: From authors' ran regressions based on authors' created dataset.

Table B4. BIN price, BIN price squared, study year, risk aversion regressed on the seller's payoff and year as interaction.

Non-linear regression of Buy-It-Now prices explaining seller's payoff + controls and interactions (R^2 = 0.18; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	1.2076717	13.3627064	0.090	0.928
BIN.price	0.9687901	0.9857650	0.983	0.328
bin_squared	-0.0099664	0.0173553	-0.574	0.567
Year.coefficient	-0.1205238	5.0567865	-0.024	0.981
Gender.coefficient	1.0748261	1.8205434	0.590	0.556
Risk aversion	0.1814698	0.3793534	0.478	0.633
BIN.price:Year.coefficient	-0.0550806	0.3770660	-0.146	0.884
bin_squared:Year.coefficient	0.0001997	0.0065709	0.030	0.976

Note: From authors' ran regressions based on authors' created dataset.

Table B5. BIN price, BIN price squared, study year, risk aversion regressed on the seller's payoff and auction type as interaction.

Non-linear regression of Buy-It-Now prices explaining seller's payoff + controls and interactions (R^2 = 0.215; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	9.495351	13.09949	0.725	0.47
BIN.price	0.660787	0.967145	0.683	0.496
bin_squared	-0.004096	0.017046	-0.24	0.811
Year.coefficient	-1.140367	4.934308	-0.231	0.818
Gender.coefficient	-0.251251	1.839146	-0.137	0.892
Auction.type	-3.570714	1.425818	-2.504	0.014
BIN.price:Year.coefficient	0.007923	0.367497	0.022	0.983
bin_squared:Year.coefficient	-0.001248	0.006408	-0.195	0.846

Note: From authors' ran regressions based on authors' created dataset.

Table B6. Round number, gender, study year, risk aversion regressed on the seller's payoff.

Linear regression of Round number explaining Buy-It-Now prices + controls (R^2 = 0.051; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	31.654	4.5205	7.002	9.9E-11
Round	-0.929	0.5275	-1.761	0.08
Gender.coefficient	-4.3915	2.4281	-1.809	0.073
Year.coefficient	0.8625	1.0436	0.826	0.41
Risk.aversion	-0.3889	0.5074	-0.766	0.445

Note: From authors' ran regressions based on authors' created dataset.

Table B7. Round number, gender, study year, risk aversion regressed on the seller's payoff and gender as interaction.

Linear regression of Round number explaining Buy-It-Now prices + controls and interactions (R^2 = 0.056; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	35.1064	6.1284	5.729	6.1E-08
Round	-1.9154	1.2934	-1.481	0.141
Gender.coefficient	-8.5344	5.5227	-1.545	0.125
Year.coefficient	0.8625	1.0448	0.826	0.411
Risk.aversion	-0.3889	0.5079	-0.766	0.445

Round:Gender.coefficient	1.1837	1.4169	0.835	0.405

Note: From authors' ran regressions based on authors' created dataset.

Table B8. Round number, gender, study year, risk aversion regressed on the seller's payoff and year as interaction.

Linear regression of Round number explaining Buy-It-Now prices + controls and interactions (R^2 = 0.053; No. of observations = 144)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	28.64071	7.07872	4.046	8.6E-05
Round	-0.06809	1.64121	-0.041	0.967
Year.coefficient	2.04802	2.38163	0.86	0.391
Gender.coefficient	-4.39145	2.43421	-1.804	0.073
Risk.aversion	-0.38888	0.50863	-0.765	0.446
Round:Year.coefficient	-0.33873	0.61129	-0.554	0.58

Note: From authors' ran regressions based on authors' created dataset.

Table B9. Correlation matrix between Round number and Gender.

Correlation_matrix	*Round*	*Gender.coefficient*
Round	1	0
Gender.coefficient	0	1

Note: From authors' ran regressions based on authors' created dataset.

Table B10. Auction type, gender, year, risk aversion regressed on seller's payoff.

Linear regression of Auction type explaining seller's payoff + controls (R^2 = 0.089; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	23.4317	3.4293	6.833	2.55E-10
Auction.type	-4.9916	1.4897	-3.351	0.001
Gender.coefficient	-1.6493	1.9014	-0.867	0.387
Year.coefficient	-1.766	0.8291	-2.13	0.035
Risk.aversion	0.327	0.3969	0.824	0.411

Note: From authors' ran regressions based on authors' created dataset.

Table B11. Auction type, gender, year, risk aversion regressed on seller's payoff and gender added also as an interaction variable with auction type.

Linear regression of Auction type explaining seller's payoff + controls and interactions (R^2 = 0.09; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**

(Intercept)	21.9708	5.3383	4.116	0.0001
Auction.type	-3.5529	4.2886	-0.828	0.409
Gender.coefficient	-0.4142	3.9431	-0.105	0.917
Year.coefficient	-1.7442	0.834	-2.091	0.038
Risk.aversion	0.4041	0.4526	0.893	0.374
Auction.type:Gender.coefficient	-1.7097	4.777	-0.358	0.721

Note: From authors' ran regressions based on authors' created dataset.

Table B12. Auction type, gender, year, risk aversion regressed on seller's payoff and year added also as an interaction variable with auction type.

Linear regression of Auction type explaining seller's payoff + controls and interactions (R^2 = 0.115; No. of observations = 141)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	26.5874	3.7568	7.077	7.27E-11
Auction.type	-13.5216	4.5967	-2.942	0.004
Year.coefficient	-3.1119	1.0702	-2.908	0.004
Gender.coefficient	-1.7248	1.8822	-0.916	0.361
Risk.aversion	0.4985	0.4025	1.239	0.218
Auction.type:Year.coefficient	3.3588	1.7144	1.959	0.052

Note: From authors' ran regressions based on authors' created dataset.

Table B13. Auction type, gender, year, risk aversion regressed on buyer's payoff.

Linear regression of Auction type explaining buyer's payoff + controls (R^2 = 0.017; No. of observations = 284)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	5.69412	2.99881	1.899	0.059
Auction.type	2.65791	1.27468	2.085	0.038
Gender.coefficient	0.37443	1.31699	0.284	0.776
Year.coefficient	-0.05766	0.80655	-0.071	0.943
Risk.aversion	-0.14357	0.46016	-0.312	0.755

Note: From authors' ran regressions based on authors' created dataset.

Table B14. Auction type, gender, year, risk aversion regressed on seller's payoff and gender added also as an interaction variable with auction type.

Linear regression of Auction type explaining buyer's payoff + controls and interactions (R^2 = 0.018; No. of observations = 284)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	6.03499	3.05609	1.975	0.049

Auction.type	1.66355	2.09739	0.793	0.428
Gender.coefficient	-0.41269	1.86401	-0.221	0.825
Year.coefficient	-0.03364	0.80851	-0.042	0.967
Risk.aversion	-0.12173	0.46215	-0.263	0.792
Auction.type:Gender.coefficient	1.56204	2.61471	0.597	0.551

Note: From authors' ran regressions based on authors' created dataset.

Table B15. Auction type, gender, year, risk aversion regressed on seller's payoff and year added also as an interaction variable with auction type.

Linear regression of Auction type explaining buyer's payoff + controls and interactions (R^2 = 0.017; No. of observations = 284)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	5.588614	3.16886	1.764	0.079
Auction.type	2.990684	3.426228	0.873	0.384
Year.coefficient	0.004357	1.001984	0.004	0.997
Gender.coefficient	0.375152	1.319398	0.284	0.776
Risk.aversion	-0.149877	0.464918	-0.322	0.747
Auction.type:Year.coefficient	-0.171962	1.642935	-0.105	0.917

Note: From authors' ran regressions based on authors' created dataset.

Table B16. Risk aversion regressed on every buyer's payoff if their highest bid would be accepted.

Linear regression of risk aversion explaining buyer's bidding strategy (R^2 = 0; No. of observations = 282)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	15.4243	2.5296	6.098	3.56E-09
Risk.aversion	-0.1287	0.5526	-0.233	0.816

Note: From authors' ran regressions based on authors' created dataset.

Table B17. Risk aversion, gender, year regressed on every buyer's payoff if their highest bid would be accepted.

Linear regression of risk aversion explaining buyer's bidding strategy + controls (R^2 = 0.002; No. of observations = 282)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	16.6868	3.5368	4.718	0.000004
Risk.aversion	-0.125	0.5696	-0.219	0.826
Gender.coefficient	-1.0948	1.6212	-0.675	0.5
Year.coefficient	-0.2929	0.9745	-0.301	0.764

Note: From authors' ran regressions based on authors' created dataset.

Table B18. Risk aversion, gender, year regressed on every buyer's payoff if their highest bid would be accepted and gender added also as an interaction variable with auction type.

Linear regression of risk aversion explaining buyer's bidding strategy + controls and interactions (R^2 = 0.004; No. of observations = 282)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	13.8218	5.8213	2.374	0.018
Risk.aversion	0.5562	1.2378	0.449	0.654
Gender.coefficient	2.5275	6.0635	0.417	0.677
Year.coefficient	-0.2823	0.9757	-0.289	0.773
Risk.aversion:Gender.coefficient	-0.8556	1.3799	-0.62	0.536

Note: From authors' ran regressions based on authors' created dataset.

Table B19. Risk aversion, gender, year regressed on every buyer's payoff if their highest bid would be accepted and year added also as an interaction variable with auction type.

Linear regression of risk aversion explaining buyer's bidding strategy + controls and interactions (R^2 = 0.019; No. of observations = 282)				
Variable	**Coefficient**	**Std error**	**T-value**	**P-value**
(Intercept)	29.5758	6.9104	4.28	0.00003
Risk.aversion	-2.9696	1.43	-2.077	0.039
Year.coefficient	-6.9112	3.2052	-2.156	0.032
Gender.coefficient	-0.8957	1.6132	-0.555	0.579
Risk.aversion:Year.coefficient	1.4858	0.6859	2.166	0.031

Note: From authors' ran regressions based on authors' created dataset.

Table B20. Breusch-Pagan Test for Heteroscedasticity of all key regressions.

Breusch-Pagan Test for Heteroscedasticity of all key regressions	
Regression	**P-value**
Buy-It-Now price regressed on Auction Type	0.32
Payoff regressed on Buy-It-Now price	3.513e-08
Payoff regressed on Auction Type (buyer)	0.034
Buy-It-Now price regressed on Round	0.819
Payoff regressed on Auction Type (seller)	0.46

Note: From authors' ran regressions based on authors' created dataset.