OPTIMAL BIDDING OVERTIME STRATEGY FOR ONLINE ART AUCTIONS: EVIDENCE FROM CHINESE ART AUCTION HOUSES

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Abstract

The paper studies the impact of bidding overtime in online art auctions. We identify two contrasting overtime bidding mechanisms influencing the final winning price: the positive effect of valuation learning and the negative effect of attention cost. We define a theoretical auction model with bidding mechanisms that yield an optimum outcome through Monte Carlo simulation. By evaluating four bidding overtime durations at six Chinese art auction houses, we consistently observe a positive effect on final prices with longer overtime policies in all settings, from which we validate the bidding mechanisms and propose an optimal design of overtime duration at 3 minutes. The paper then discusses whether these effects apply to lower-value eBay auctions and physical auctions.

Keywords:

Online Auctions, Competition Dynamics, Traditional Chinese Arts, Digital Transformation, IT Strategies.

Implementation Software:

Python 3.11.5 (Matplotlib 3.7.1, NumPy 1.24.2, Pandas 1.5.3, Seaborn 0.13.0),

Stata 17.0.

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1 Introduction

1.1 Research Overview

In recent years, the art auction industry in China has witnessed substantial growth. The COVID-19 pandemic reformed the entire industry landscape through a far-reaching digital transformation, and as a result, online art auctions have become mainstream. One notable feature of online auction platforms is the utilization of "overtime", which refers to the automatic extension of the auction deadline when bids are submitted close to the original closing time. Bidding overtime is well-researched for its effectiveness in preventing auction sniping and promoting fair competition. However, no published literature exists on optimal overtime duration policies and the overtime extension's impact on final prices and auction house profitability. This study, therefore, fulfils the gap for the auction industry by theoretically and empirically demonstrating the underlying bidding mechanisms and providing optimal overtime durations to increase auction house revenue.

This research addresses two common questions from the auction houses: "How does the bidding overtime affect the competition and winning price?" and "To maximise the revenue (by winning price) of the auction house, what would be the optimal design of the overtime duration?" Our model incorporates varying bidding mechanisms to quantify specific impacts during the active bidding stage, and we subsequently validate our model hypotheses using empirical data from Chinese art auction houses.

Our research complements existing knowledge on online auctions and bidding overtime. We adopt the bidding mechanisms by Reddy & Dass (2006) that emphasise competition in price formation near the deadline. We also build upon Plattner's (1998) work on the inherent uncertainty associated with artworks. We refer to the auction duration problems and construct the theoretical model of an auction with bidding mechanisms. Monte Carlo simulations show that there exists an optimal overtime policy that yields the highest profit.

We hypothesise two dominant bidding mechanisms in the overtime period. When overtime durations increase, under the uncertainty assumption, bidders have more time to consider and update their valuations from the competition, as "learning from price", which increases the final price. However, longer overtime policies result in longer auction durations, which result in higher "attention costs" that offset the increase in price. The two mechanisms combine to form an optimal overtime policy under our theoretical model, generating the highest auction house profits.

Empirically, we meticulously collected and processed a unique dataset from 6 Chinese art auction houses with four overtime durations for a total of 667 overtime items in 1851 auction records. We invited four experts to score and select items to mitigate the effect of item level heterogeneity. Reduced form regressions across six settings and three subsets consistently validate our hypotheses and suggest that the overtime effect on price growth is most significant in the 3-minute overtime policy. Therefore, we propose policy recommendations to art auction houses to use 3-minute overtime in future auctions.

The remainder of the paper is organised as follows: Section 1 introduces the institutional background of the Chinese art auction market. Section 2 shows the rationale for overtime bidding and the bidding mechanisms known in the literature. Section 3 presents a theoretical auction model with bidding mechanisms and uses simulations to show the results and formulate hypotheses. Section 4 explains the collection and processing of the empirical data in use. Section 5 performs reduced-form regression and further corroborates the hypotheses through empirical observations. Section 6 discusses the scalability of this mechanism to other auction types. Section 7 summarises the research on optimal bidding overtime strategies and lists the limitations and future directions.

1.2 Institutional Background

Chinese Art Auctions: Fundamental Characteristics

In recent years, the global art and antiquities market has experienced substantial growth as demand surges for these non-renewable human heritages. The scarcity of high-quality artworks has led to exorbitant transaction prices and many fakes and imitations on the market. Auction is the mainstream transaction method for high-quality artworks. Plattner (1998) described the art market as one where goods were nearly impossible to value, and demand was unpredictable. A fixed-pricing system would be unsuitable for the art market, whereas auctions are better at uncovering the highest valuations to facilitate the best deals.

As a country with a prosperous ancient culture and substantial economic growth, China is an emerging market for art auctions, especially in Chinese traditional art and antiques. In 2021, the total sales of traditional Chinese artworks have been US$5.9 billion, with a robust year-on-year increase of 36%, accounting for 79% of the total global sales of this market (Artnet Worldwide Corporation, 2022).

The Chinese art auction market is highly regulated, with significant entry barriers and strong regulations. The industry landscape is characterised by over a dozen large art auction houses and clusters of smaller auction houses in each province, each specialising in distinct regional niches. Among the leading auction houses are China Guardian (Beijing, CN), Poly (Beijing, CN), Xiling Yinshe (Hangzhou, CN) and Duoyunxuan (Shanghai, CN) (China Brands Network, 2023). In addition, many international auction giants such as Christie's (London, UK) and Sotheby's (New York, USA) have regional branches. They are also market leaders in the Chinese traditional art market (China Brands Network, 2023).

Traditional Chinese art auction houses strictly follow the English auction format when selling art and antiques. Until 2019, most auction houses relied on the purely offline business model: In an auction, they would publish and distribute auction item catalogues, conduct on-site preview sessions for 2-3 days, and then host physical auctions in key cities of China. The auction houses profit by charging commissions to buyers and sellers, usually at 10%-15% of the final price to each side. For instance, a 12% commission rate on an item selling for $1,000 would yield a total gross profit of $240.

COVID-19 has resulted in an unanticipated digital transformation towards online art auctions. The social distancing restrictions led to the complete suspension of on-site auctions, forcing art auction houses to switch auctions online. After the pandemic, while in-person auctions resumed, most auction houses have retained online auctions as they view them as a valuable revenue stream. Online art auctions are cost-effective, more flexible, and appeal to a broader and younger audience.

<u>The Buyer Side</u>

Most buyers at Chinese art auctions come from economically advanced regions, mainly concentrated in coastal China and major metropolises such as Beijing, Shanghai, Guangzhou, and Hong Kong. These buyers can be broadly divided into two distinct segments: public and private. Public buyers are represented by national collecting institutions and large consortiums like the Palace Museum (Beijing, CN) and Shanghai Museum (Shanghai, CN). They procure numerous ancient Chinese artefacts, home and abroad, to preserve Chinese cultural heritage. These public buyers typically have fixed valuations for the artworks they choose to bid on.

Private buyers, who would be the key audience of the online art auctions of our research, are represented by various individual collectors, ranging from prominent, seasoned collectors and scholars to pure speculators. While a genuine passion for art drives some private buyers, others purely focus on the potential for monetary returns. Private buyers typically have less deterministic purchasing patterns and item valuations, making them more susceptible to bidding dynamics and the auction process.

2 Literature Review

2.1 Auction Snipping and Bidding Overtime

A well-identified side effect of fixed-deadline online auctions, especially eBay auctions, is known as auction snipping, where overtime bidding is seen as a viable solution. Roth & Ockenfels (2000) first proposed the auction snipping behaviour, i.e., placing bids as late as possible, as a rational response to fixed-deadline online auctions through a natural experiment between eBay and Amazon. They found that late bidding attempts were distributed according to the power law before closing. They also identified such behaviour in higher value auctions of antiques, where late bidders build up knowledge towards actual item values based on the earlier bids. Bidders would be incentivised to bid late as expert bidders would avoid the leakage of item valuations, and non-expert bidders would avoid setting off price wars (Roth & Ockenfels, 2000).

Further research signified the drawbacks of auction snipping. Yang & Kahng (2006) explored bidding data on eBay and concluded that late bidders placing a single bid are more likely to win than incremental bidders. They proposed a negative relationship between winning probability and bidding frequency with statistical significance. Gary (2007) conducted a field experiment and found a $1 average benefit to auction snippers on eBay per item. Backus et al. (2015) formalised the conceptual ideas of snipping. They identified a sizable discouragement of new bidders from participating in future auctions, causing the auction platform to suffer from an economically significant market size loss.

However, only some researchers have touched on the possible solutions to prevent auction snipping. Trevatan et al. (2011) proposed an amendment to the online auction format to introduce an undisclosed timeout extension when new bids are received before closing, allowing bidders to reveal their actual valuations of the items. This method, known as bidding overtime, has since become a common practice in the online auction industry. Wang & Hao

(2022) studied the benefits of increasing deadline uncertainty through a multiplayer continuous-time revision game. They suggested that eBay bidders' decision-making follows a stochastic Poisson process, and with increasing deadline uncertainty, bidders would become more risk-averse, which, in turn, could promote competition. Nonetheless, no published research has determined theoretically or empirically the optimal duration of each bidding overtime extension. In addition, no known literature has examined whether changing the overtime duration can enhance an auction's competition dynamics, thereby increasing the final price and profitability of the auction house.

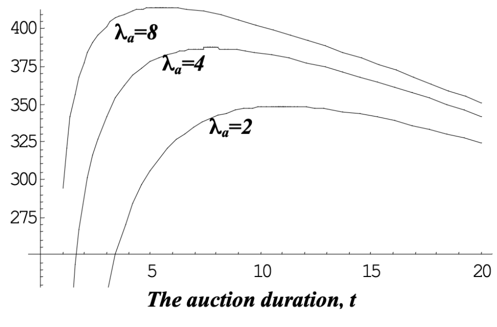
2.2 Bidding Mechanisms

Optional Auction Duration

Practically, optimal bidding overtime can be viewed as a variant of the optimal auction duration problem, which has been extensively studied in multiple online auction settings. Haruvy & Leszczyc (2009) presented a commonly believed trade-off whereby longer auctions might lead to more bidders and higher prices, while shorter auctions might attract impatient bidders and provide more competition dynamics. Empirically, with an increase in auction duration, eBay items showed an increase in final price by about 11%. In comparison, articles on a much smaller local auction site saw a 20% decrease in the final price since the bidder increase effect is insignificant (Haruvy & Leszczyc, 2009).

Vakrat & Seidmann (2000) proposed a theoretical model that introduced uncertainty in bidders' decisions based on site traffic, auction duration, and the number of items offered through a non-stationary Poisson process. They suggested an optimal auction duration of about 5 minutes. As in Figure 2.1, the higher the site traffic, the higher the profit, and the shorter the optimal auction duration (Vakrat & Seidmann, 2000).

Figure 2.1: Auctioneer's Profit by Auction Duration and Site Traffic (λ)



Source: Figure 6a, Implications of the Bidders' Arrival Process on the Design of Online Auctions (Vakrat & Seidmann, 2000)

Nonetheless, the effect of auction duration can be less apparent, as research suggests varying results in other auction settings and empirical data. Mithas & Jones (2009) showed that auction duration had no significant impact using data from online procurement auctions. Ren & Chen (2020) adopted an independent private value model and proposed that over a specific duration, the seller's expected revenue would decrease monotonically due to a higher increase in costs than the increment of bidders.

Known Bidding Mechanisms

While item characteristics (item level heterogeneity), such as artist reputation and item quality, would be significant to the final pricing when considering auction outcomes, the competition throughout the bidding process was also substantial (Reddy & Dass, 2006). Reddy & Dass (2006) further illustrated that the item-characteristic effects were more pronounced at the auction's beginning while bidding dynamics and competition effects became dominant at the ending phase – more relevant to the overtime extension period. Behavioural mechanisms, such as the "winner's curse" proposed by Kagel & Levin (1986), whereby auction winners tend to be overly optimistic and pay more than the actual values, are also common in situations where there are many bidders, and the bidding is intense. Furthermore, Haruvy & Leszczyc (2009) emphasised that a trade-off might exist in determining the optimal auction duration based on audience size and competition dynamics.

Table 2.1 lists the above factors and other notable mechanisms proposed by past literature and the auction houses in collaboration.

Table 2.1: Known Bidding Mechanisms of Auction Duration

Side of Impact	Name	Source	Note
Item Level Heterogeneity	Artist Reputation	Reddy & Dass, 2006	Diminishing at the end
	Historical Price	Reddy & Dass, 2006	Diminishing at the end
	Item Quality	Reddy & Dass, 2006	Diminishing at the end
	Starting Bid	Reddy & Dass, 2006	Diminishing at the end
	Expert knowledge / Auction House Expertise	Kalbermatten & Rausch, 2021	

Side of Impact	Name	Source	Note
Competition – Time Invariant	Number of Bids & Bidders	Reddy & Dass, 2006	
	Unit Location in Auction	Reddy & Dass, 2006	Diminishing at the end
	Bidder Experience	Srinivasan & Wang, 2010	
	Bidder Patience	Watts, 2019	
Competition – Longer Preferred	Audience Size Growth	Haruvy & Leszczyc, 2009	
	Disappointment from Lose / Exit	Backus et al., 2015	As a negative impact for short periods, less sensitive to experienced bidders.
	Sever & Technical Capacity	Auction House	
Competition – Shorter Preferred	Competition Dynamics	Haruvy & Leszczyc, 2009	
	Bidding Velocity (Frequency)	Reddy & Dass, 2006	Closer to the end
	Irrational Follower Bids	Auction House	
Competition – Unimodal	Buyer Value Dispersion	Vakrat & Seidmann, 2000	By empirical examination

Source: Various literature and auction houses in collaboration.

Given the uncertain nature of artworks, the dynamics of auction prices and bidder valuations are complex and challenging to quantify. Existing literature and auction house experience propose that the optimal auction length depends on a delicate balance between short-term and long-term. We extend this conclusion to overtime and make assumptions that the following mechanisms dominate the bidder's bidding process:

(1) When the price of an item is higher than the bidder's valuation, bidders will learn from the current price and raise their valuation out of excitement, fear of disappointment or pure irrationality with a certain probability, which is determined by the current bidder's profit (difference in price and valuation) and urgency (remaining bidding time).

(2) Bidders face attention costs (opportunity costs of time), which would discourage longer overtime settings due to the resulting longer auction durations.

3 Model

3.1 Presumptions

Perfectly Rational Outcome

We first consider the case where all bidders have a unique and predetermined item valuation and are perfectly rational regardless of the bidding dynamics. In a classical English auction, the winner is the bidder with the highest valuation. At any overtime duration setup, his/her valuation remains unchanged at any time, and there will be a Nash Equilibrium final price. Other bidders will exit when the present bid exceeds their own valuations. Therefore, we derive the following conclusions under perfectly rational conditions:

(1) The overtime duration does not impact perfectly rational bidders with fixed item valuations.
(2) The overtime duration does not impact deterministic value items.

On top of that, we expand our rational assumptions under specific edge-case scenarios:

The rational strategy for ultra-short overtime durations would be auction sniping, where bidders shall strategically hide their bids until the last moment, leading to imperfect competition and limited knowledge of an item's value (Roth & Ockenfels, 2000).

(3) A zero / ultra-short overtime duration will have lower and suboptimal final prices than the rational outcome.

For ultra-long overtime durations, when bidders have unlimited decision-making time, they will have enough time to confirm their beliefs. Therefore, the valuation learning process will terminate as all possible information can eventually be exploited. Thus, even bidders who are initially irrational will behave become deterministic and rational as the bidding overtime goes to infinity.

(4) An infinite overtime duration will converge to the rational outcome, regardless of initial rationality conditions.

However, purely rational outcomes are unlikely to exist in art auctions. Due to the inherent uncertainty of art and antiques, most items will never meet these rational conditions, and many bidders do not have a precise and deterministic valuation (Beckert & Rössel, 2013). Thus, bidding dynamics significantly affect valuation formation and final price (Reddy & Dass, 2006).

Presumptions on Bidding Dynamics

Based on our observations on online art auctions, we identify a common price growth path and bidding pattern characterised by two distinct stages, regardless of bidder profiles and whether the item enters overtime.

(1) Early bidding stage:

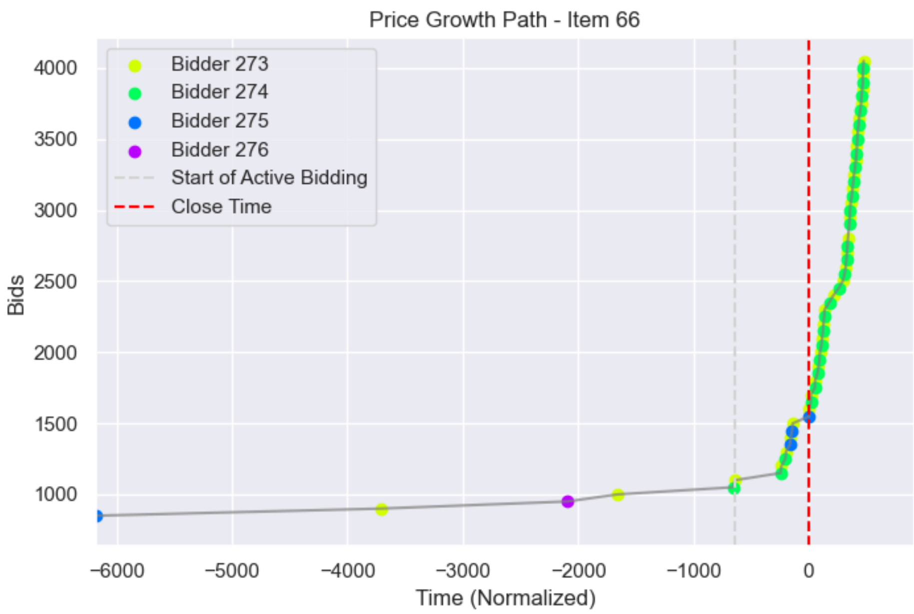
When the item is far from the scheduled closing time, there are infrequent bids, and the bids have lower prices. Bidders' decisions are generally independent and unrelated to time.

(2) Active bidding stage:

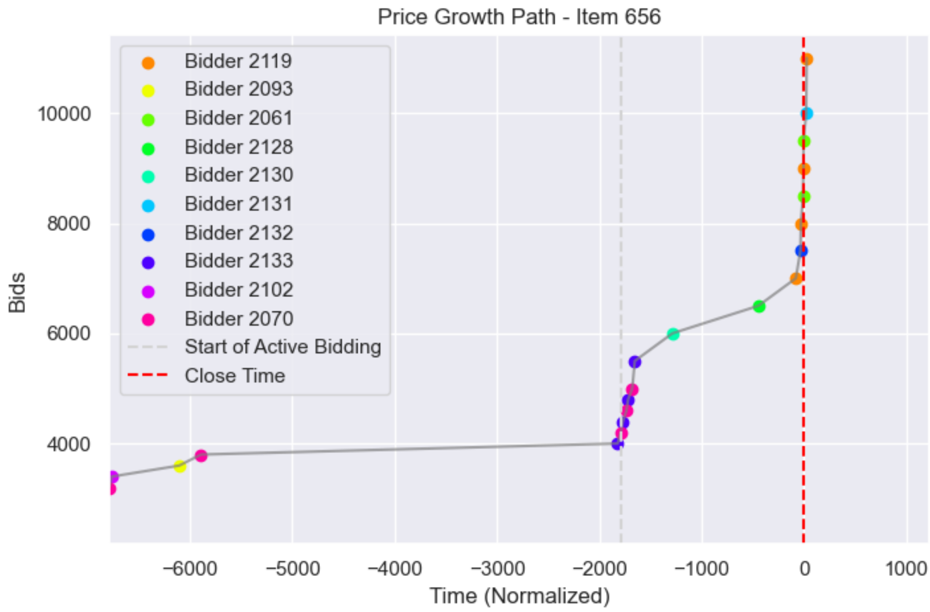
When the item approaches its closing time, bidding becomes more intense, and the price rises rapidly. As bidders now focus on the ongoing auction, this stage is critical to final price formation and auction house's revenue. When item values are uncertain, multiple irrational bidding mechanisms like learning and blind following will be prevalent here.

Figure 3.1 visualises the price growth path in two stages from two typical auction items. We define the active bidding stage in the charts by all subsequent bids having intervals of less than 15 minutes (900 seconds). The original deadline is normalised to 0 and all other bidding times show the time difference in seconds. The first item has two dominant bidders in the active bidding stage, while the second item sees involvement of multiple final competitors.

Figures 3.1: Typical Price Growth Path for Online Art Auctions



Note: Item 66 is LOT19 (ancient literature) from auction house 1, auction 8 with a 3-minute overtime.



Note: Item 656 is item 145050(drawing) from auction house 3, auction 3 with a 1-minute overtime.

In terms of bidding decisions in the active bidding stage, we classify three common bidding behaviours according to the bidding interval: (1) Followers, (2) Decision-makers, (3) Snippers.

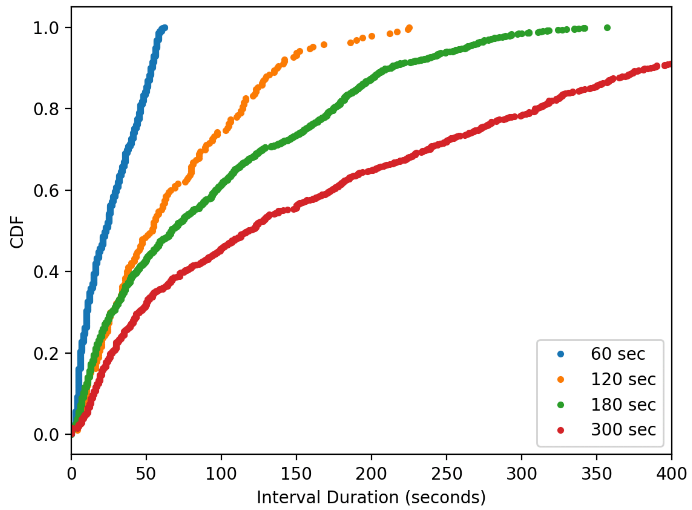
Followers place bids immediately after observing new bids from other participants. Given the immediate decision to react, the current price shall be significantly lower than the follower's valuation ceiling. Therefore, we assume that bids will be made immediately during the active bidding phase when the price is considerably lower than the bidder's current valuation.

Decision-makers bid after a consideration period, during which they are influenced by behavioural mechanisms and may learn from the current price. Bidders typically act as decision-makers when prices are close to their valuations.

Snippers make last-minute bids to hide their valuations from competitors. When the consideration period becomes too long, the delay is purely strategic, and the bidder still has residual profit to bid based on the current price and valuation.

The cumulative distribution chart on bidding intervals from the active bidding stage reveals a consistent composition for each bidding type under all overtime policies: We use turning points in CDFs to hypothesize structural changes in bidding types. In estimate, followers account for 30% of the total bid, while snipers account for 10%. Decision makers account for the remaining 60% of bids. The change of slope is less significant in short overtime.

Figure 3.2: Cumulative Distributions of Bidding Intervals



Following the presumptions on bidding dynamics, we relax the perfect rationality condition and allow indeterministic bidder valuations. We then propose the following behavioural mechanisms to apply based on the assumptions inferred from the literature on auction durations in Section 2.2:

<u>Strictly Increasing Valuations:</u> The bidder's valuation is strictly incremental. The bidder will withdraw from the auction when the estimated winning profit is significantly negative.

<u>Probabilistic Bidding:</u> Bidders decide whether to bid at a particular time by a Bernoulli probability that considers urgency (as snippers) and the bidder's expected winning profit (as followers).

<u>Learning from Price:</u> When the current expected winning profit is positive, bidders may, at a defined probability, update their valuations to align with the price at a margin (decision makers).

<u>Attention Cost:</u> All bidders have a quadratic attention cost over time. Thus, the cost for participation in shorter auctions is not significant, while long enough auctions will effectively end the auction, as the winner's total profit can become negative.

3.2 Auction with Bidding Mechanisms

We propose an English auction with bidding mechanisms through valuation learning and competitive dynamics.

We assume the item's true value V is completely unobservable. Each bidder i would have an initial valuation $EV_{i,0}$ based on his/her best information. The bidder's valuations $EV_{i,t}$ updates with time.

$$EV_{i,0} \Leftarrow info(i)$$

The auction commences from the active bidding stage, with initial price $P_0 = 0$, start time $t = 0$, and n bidders. P and t are stepwise and normalised. Bids are denoted by a binary parameter b_{t+1}:

$$P_{t+1} = P_t + 1 * b_{t+1}$$

The auction terminates when the price remains unchanged after a countdown of k seconds, from which the final P^* and t^* are derived. k represents the real-world overtime duration policy.

$$P^* = P_{t+k} = P_t$$
$$t^* = t + k$$

Bidders update their valuations at each t through valuation learning from price. p is the probability of the bidder being a learner. $\varepsilon(i)$ is the random valuation margin following a Poisson (i) process.

$$EV_{i,t+1} = P_t + 1 + \varepsilon(i) \quad at\ probability\ p, if\ EV_{i,t} < P_t + 1$$
$$EV_{i,t+1} = EV_{i,t} \quad for\ all\ other\ cases$$

Each bidder calculates the expected winning profit $\pi_{i,t}$ based on $EV_{i,t}$, the current price and opportunity cost of time. γ_i is the bidder's attention cost per time unit.

$$\pi_{i,t} = EV_{i,t} - (P_t + 1) - \gamma_i t^2$$

We then use $s_{i,t}$ to represent a Bernoulli probability by bidder i to place a bid at time t. Bidding decisions become deterministic at negative or sufficiently large $\pi_{i,t}$ values. θ denotes a deterministic bound at high profits.

$$s_{i,t} = 0 \quad when\ \pi_{i,t} \leq 0$$
$$s_{i,t} = 1 \quad when\ \pi_{i,t} \geq \theta EV_{i,t} \geq 0$$

Bidding probability is determined by urgency, expected winning profit, and noise of randomly holding the bids (as a snipper). k_{remain} is the remaining time under countdown k. τ is the snipping parameter representing the probability of randomly delaying the bid. The bidding decision is deterministic when $s_{i,t}$ is outside the range $(0, 1)$.

$$s_{i,t+1}(\pi_{i,t}) = \ln(\pi_{i,t} + 1) / \ln(\mathrm{k_{remain}} + 2) * (1 - \tau)$$

A bid will be made if any bidder's Bernoulli $(s_{i,t})$ draw is positive. One bidder is randomly selected in cases of multiple bids. The auction continues to $t + 1$, and the above process will be repeated.

$$b_t = 1 \; if \; \exists draw(s_{i,t}) = 1$$
$$b_t = 0 \; if \; \exists draw(s_{i,t}) = 0$$

The auction house profit Π is a linear transformation of P^* and t^*. φ is the profit markup on the final price (commission fee), and γ_h is the duration cost of the auction house considering the aggregated operational costs, labour, and platform charges during the auction. We then derive the optimal overtime policy k^* given parameter sets, which maximises Π.

$$\max_{\mathrm{k}} \Pi = \varphi P^*(k, n, \gamma) - \gamma_h \mathrm{t}^{*2}$$

3.3 Model Simulation

Parameters Inference

For simplicity, we reduce the auction to having only two bidders. According to our data, in many cases, there are only two main bidders in the active bidding stage. In theory, bidders are likely to withdraw from an auction when their valuation is significantly lower than the current price. If multiple bidders have similar initial valuations, the bidding mechanism should be the same. This will lead to more intense competition, and the final price shall be higher, but it will not have a significant impact on the overtime effect.

Most parameters in this model can be tuned. The consistent patterns and optimums can be simulated and verified under various parameter settings. We provide our inference on the parameter values based on current data, convention, and auction house knowledge, which is summarised in Table 3.1.

We provide a Python-based Monte Carlo simulator that can simulate and visualize the results of a given set of parameters. An explanation of its usage is located within the code package.

Table 3.1: Inference of Model Parameters

Parameter	Parameter Name	Value	Inference on Value
γ_i	Bidder's attention cost	0.0003	Attention cost shall be close to 0 at smaller durations under the quadratic assumption. Can be tuned.
$\imath$	Markup on learning	3	We assume a Poisson (3) distribution. Bidders need at least 1 step markup to win the auction again when he/she places the bid. 2-5 are all valid assumptions.
θ	Deterministic bound	0.8	We assume bidders are rational when the profit is over 80% of their expected valuations, without valuation learning. Can be tuned.
p	Learning Probability	0.6	Inferred from the percentage of intermediate bidding intervals in Figure 3.2.
τ	Snipping Probability	0.1	Inferred from the percentage of larger bidding intervals in Figure 3.2.
φ	Auction house profit markup	0.24	We combine the conventional commission fees from auction houses on buyers (12%) and sellers (12%).
γ_h	Auction house duration cost	0.0005	We assume a slightly larger platform and labour cost in online auctions than bidders. Can be tuned.

The following analysis presents the model outcome using our inferred values of model parameters.

Simulation Outcome

Given the mathematical complexity of the model, we employ the Monte Carlo simulation approach to solve the auction. For each set of parameters, we iteratively run 1000 rounds for each countdown time policy k. We then observe the average final price P^* and auction house profit Π.

We observe consistent patterns emerge across various parameter sets. When k increases, P^* experiences significant growth and gradually declines after the peak. Π declines more sharply and eventually becomes negative. The optimum by Π tends to be marginally smaller than P^*, possibly due to attention costs on increased time. As Π is unobservable from empirical data, we shall prioritise a marginally smaller k policy than the optimum given by P^*.

The following figures visualise the simulation outcome under our inferred parameter values. Figure 3.3 shows that the optimal policies of k are 5 for Π and 8 for P^*, given the same initial valuations $EV_{1,0} = EV_{2,0} = 10$.

Figure 3.3: Monte Carlo Simulation Outcome on Inferred Parameter Set

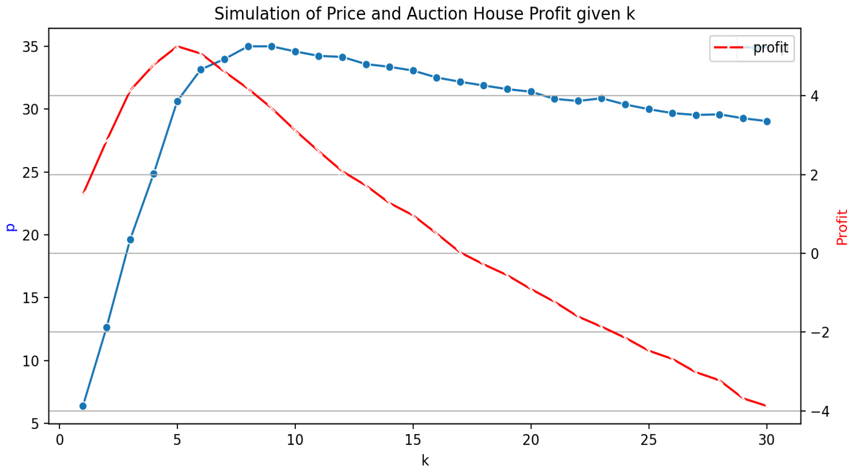
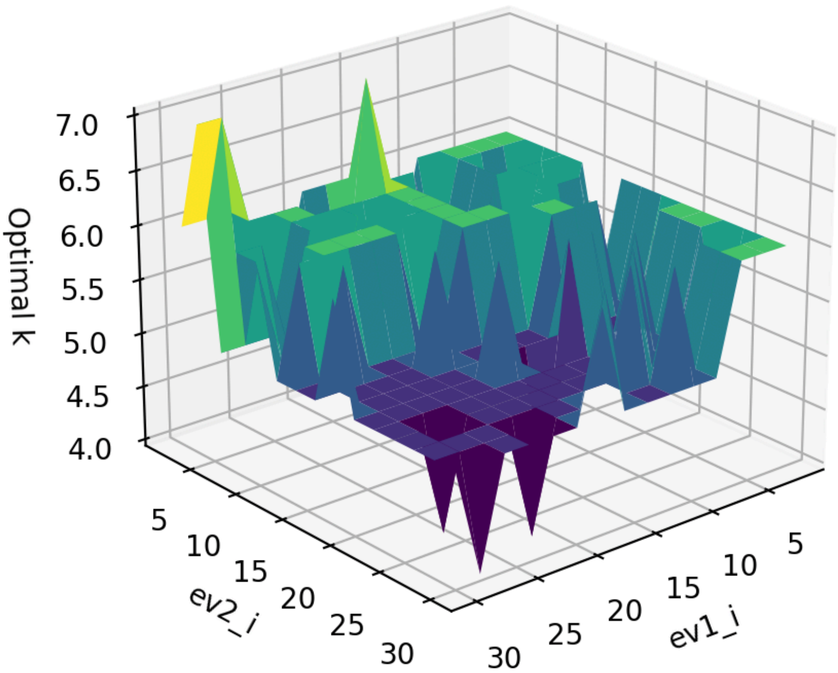


Figure 3.4 examines the optimal k hyperplane at multiple $EV_{i,0}$ settings. The k values exhibit a degree of stationarity, with only marginal declines as the initial valuations increase. As P in the model represents large price level increments, we believe k is unlikely to exhibit significant variations.

Figure 3.4: Hyperplane of the Optimal Policy of k and Initial Valuations



3.4 Hypothesis

As the model findings are consistent under multiple parameter sets, we propose the following two hypotheses, explaining the tension from both sides towards the peak, to be verified in our empirical data:

<u>Hypothesis 1:</u> Increasing the overtime duration in online auctions leads to a higher final price, as there are more instances of bidders learning from the prices to increase their valuations. This effect is more prevalent in shorter overtime policies.

<u>Hypothesis 2:</u> Extended overtime durations in online auctions leads to a lower final price, as they discourage bidder participation due to increased attention costs. This effect is more prevalent in longer overtime policies.

4 Data

4.1 Data Source

To empirically validate the two hypotheses, we have spent considerable time and effort liaising and collaborating with multiple art auction houses to obtain detailed online auction bidding data. All six auction houses we select have a satisfactory market presence in traditional Chinese art auctions and a strong history in auctioning respectable artefacts through market research. Due to anonymity and regulatory requirements, we use serial numbers to replace the names of auction houses and their respective auction items. The auction houses have followed applicable laws and removed sensitive information in the dataset.

The final data we provide comes from six art auction houses based in mainland China. All six auction houses selected are traditional auction houses that have undergone digital transformation in recent years and now use online auctions as a major source of revenue. Table 4.1 provides the background information on these art auction houses.

Table 4.1: Background of the Art Auction Houses

Auction House	1	2	3	4	5	6
Ownership	State-Owned	Private	State-Owned	Private	Private	State-Owned
Size	Medium	Medium	Large	Medium	Medium	Large
Location	Shanghai	Shanghai	Shanghai	Beijing	Jiangsu	Zhejiang

Auction House	1	2	3	4	5	6
Year Starting Online Auctions	2019	2022	2019	2018	2018	2016
Annual Physical Auctions	2	2	4	4	4	2
Annual Online Auctions	20-50	10-20	20-50	100-200	10-20	300-400
Annual Items (Estimate)	1000-2000	2000-3000	10000-20000	8000-10000	3000-5000	20000-30000
Auction Specialisation	Calligraphy, Ancient Books	Calligraphy	Calligraphy, Paintings	Paintings	Paintings	Paintings, Ancient Books, Ink Rubbings
Overtime Duration	180s	120s	60s	300s	300s	180s

Source: Auction houses in collaboration

All the art auction houses here follow the classical English auction format. In their online auctions, every item listed is provided with a pre-declared starting price, scheduled closing time, and item information. Buyers who pay a deposit can participate in this online auction. Bids are ascending and according to a defined price gap. All bids placed are publicly displayed on the auction page. If there are incoming bids about 1-5 minutes before the scheduled closing time, the item will trigger bidding overtime, and the bidding deadline will be extended by 1-5 minutes respectively. We note a minor variation on auction houses on overtime formats, fixed block extension or dynamic extension, which is illustrated via two examples in Table 4.2:

Table 4.2: Comparison between Two Overtime Extension Formats

Auction House 1, 2, 4, 5	Auction House 3, 6
Format 1: Fixed Block Extension	Format 2: Dynamic Extension
3min Overtime, Scheduled close at 5:00 pm	3min overtime, Scheduled close at 5:00 pm
Any bid in 4:57 – 5:00 => New close at 5:03 pm	Bid at 4:59:32 => New close time at 5:02:32
Any bid in 5:00 – 5:03 => New close at 5:06 pm	Bid at 5:01:16 => New close time at 5:04:16
Any bid in 5:03 – 5:06 => New close at 5:09 pm	Bid at 5:04:11 => New close time at 5:07:11
No bid in 5:06– 5:09 => Item closed at 5:09 pm	No new bids => Item closed at 5:07:11

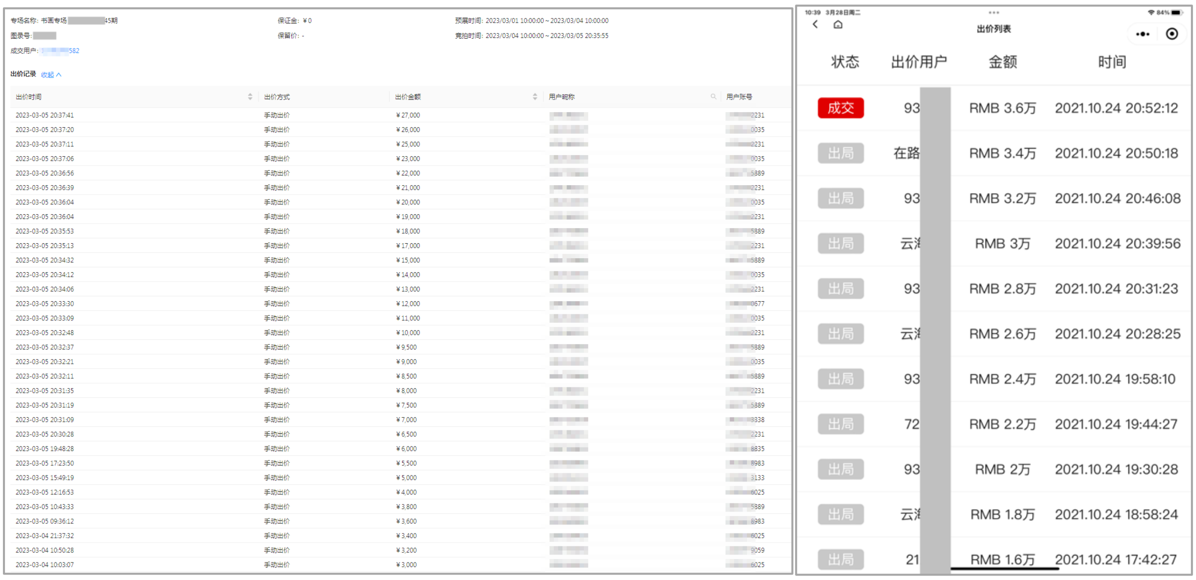
In practice, since the extreme cases under both formats only produce a one-step difference, we will not consider this format difference to be significant to the results of our empirical studies.

4.2 Data Processing

The raw bidding data come primarily in two different formats, as shown in Figures 4.1 and 4.2:

(1) Online auction system screenshots for each item. Screenshots include bidding history with bidder, bidding price, and timestamp for each bid. Items under this format are manually inputted, processed, and validated.

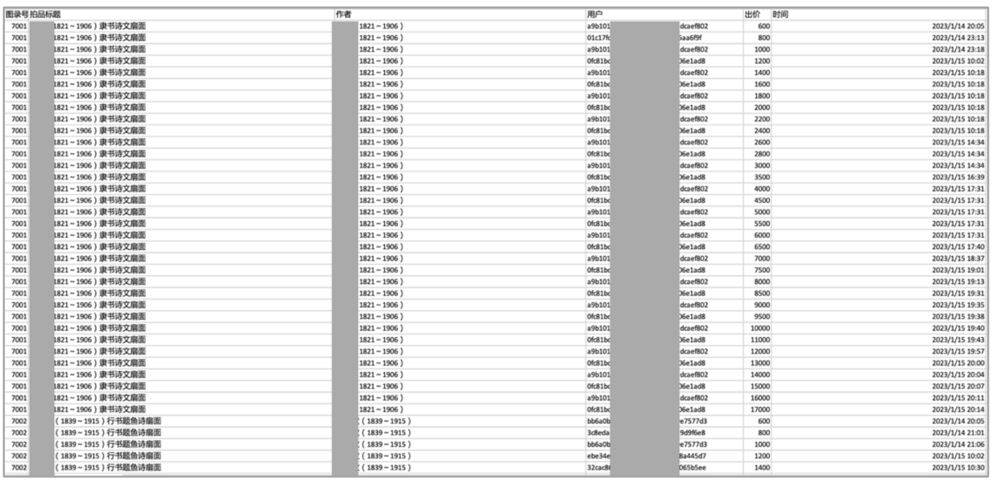
Figures 4.1: Raw Data Formats – Online Auction System Screenshots



Source: Auction houses in collaboration

(2) Directly exported bidding data in xlsx format from the server. Items under this format are automatically processed and validated in the pipeline.

Figure 4.2: Raw Data Formats – Directly Exported Datasets



Source: Auction houses in collaboration

The raw data pass through a self-written Python automation pipeline to standardise and check for abnormalities. In the first stage, data from these two formats are pre-processed using the auction data parser, which supports both data formats, and are cleaned. Timestamps are converted into the Unix timestamp format. All data go through a data validator to identify potential input errors and data issues, which are then manually corrected. The raw data, after removing sensitive and confidential information, is exported to a human-readable wide-form spreadsheet "1_public_full_dataset.xlsx" in the code package. As an example of the processed auction dataset format, Table 4.3 shows item 2's partial bidding history in the overtime stage.

Table 4.3: An Example of Processed Raw Auction Dataset – Item 2

Auction House	Auction ID	Item ID	Overtime Policy	Scheduled Closing Time	Bidder ID	Bid Amount	Bid Timestamp	Notes
……								
1	1001	0002	180	2021-11-06 20:42:00	2	4000	2021-11-06 20:43:10	
1	1001	0002	180	2021-11-06 20:42:00	3	4100	2021-11-06 20:43:19	
1	1001	0002	180	2021-11-06 20:42:00	2	4200	2021-11-06 20:43:29	
1	1001	0002	180	2021-11-06 20:42:00	3	4300	2021-11-06 20:46:36	
1	1001	0002	180	2021-11-06 20:42:00	2	4400	2021-11-06 20:47:10	Winning Bid

In the second stage, the Python pipeline calculates and generates several critical auction and item parameters, including the identification of unique bidders over a global Python dictionary, and length and bids of overtime, etc. The processed database is stored and exported for analysis, which is provided in the code package as "2_processed_full_dataset.xlsx".

To balance item volumes under each overtime and reduce the workload for experts, we use random sampling to reduce overtime items to half from the 3-minute overtime duration. This creates a similar quantity of overtime items in most policies (Except for 120-second data, which are limited). The data is then combined with the rest of the auction data in the final data table.

We then invite four experts to manually score each sampled overtime item from 0 to 9 (10 values) and perform item recommendations. The expert scores and recommendations are combined into "3_processed_sample_dataset.xlsx" in the code package.

After more than four months of data collection, we believe that, to the best of our and auction houses' current knowledge, this overtime dataset is the first-ever available dataset centred on the online art auction items with bidding overtimes, making our research unique and innovative.

4.3 Descriptive Statistics

The target value of our research is the final price P^*. The statistics of the dataset and its items from each overtime duration are summarised in Tables 4.4. There are 1851 recorded items in total, while the overtime items sampled for analysis are 667.

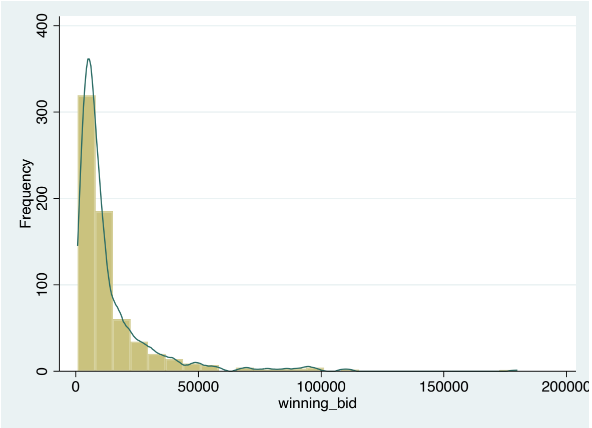
Tables 4.4: Summary of Data

Overtime Policy	All Items	Overtime Items	Final Sample
1min (60sec)	407	219	219
2min (120sec)	100	41	41
3min (180sec)	1040	462	231
5min (300sec)	304	176	176
Total	1851	898	667

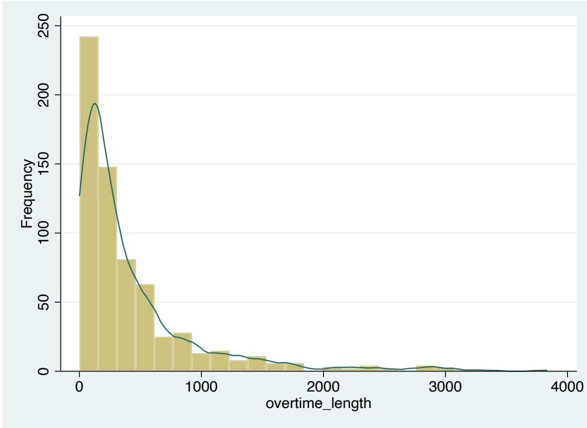
Data	Variable	Mean	Median	Std. Dev.	Min	Max
All Items (1851)	Winning Bid	10261.43	6000	14192.85	200	180000
	Bid bef. Scheduled Close	6235.64	3000	10191.24	0	150000
	Total Bids	14.08	12	10.19	1	76
	Normal Bids	11.36	9	8.13	0	56
	Normal Time Bidders	4.58	4	2.48	0	17
	Overtime New Bidders	0.21	0	0.55	0	6
Overtime Items (667)	Winning Bid	13697.08	8000	17491.07	750	180000
	Bid bef. Scheduled Close	9655.47	5500	12524.84	500	96000
	Overtime Length (seconds)	428.97	233	552.57	1	3834
	Overtime Bids	5.51	4	5.43	1	50
	Overtime New Bidders	0.48	0	0.36	0	6
	Combined Expert Score	30.28	27.5	15.21	5	80

Figure 4.3 visually demonstrates the distribution of important empirical data parameters. Apart from the overtime effect, our data aligns with the domain knowledge on art auctions. Figure 4.3 visually demonstrates the distribution of important empirical data parameters. We observe one-tailed distributions for final price, total overtime, and semi-normal distributions for total bids and average expert scores. The final price is also positively correlated with the amount of the last bid before the original deadline in our data.

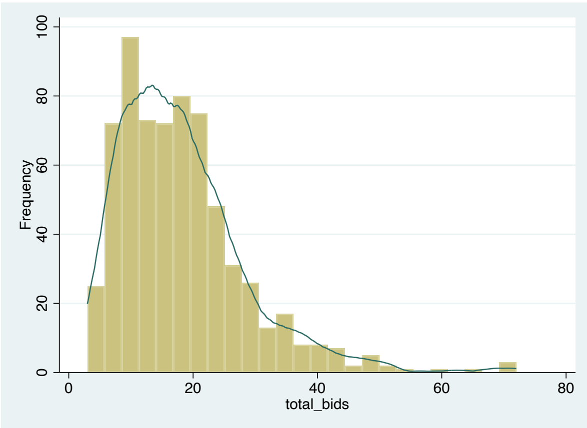
Figures 4.3: Data Visualisations



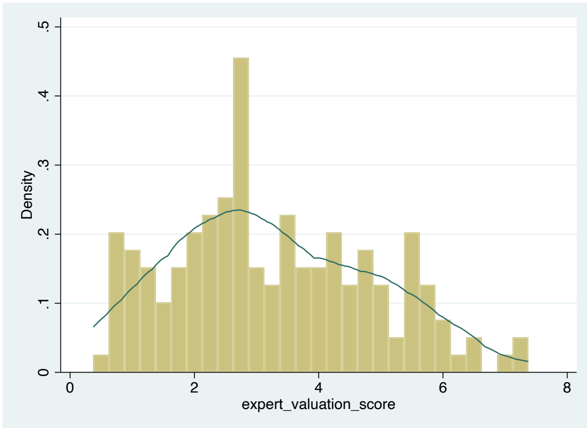
Distribution of the final price



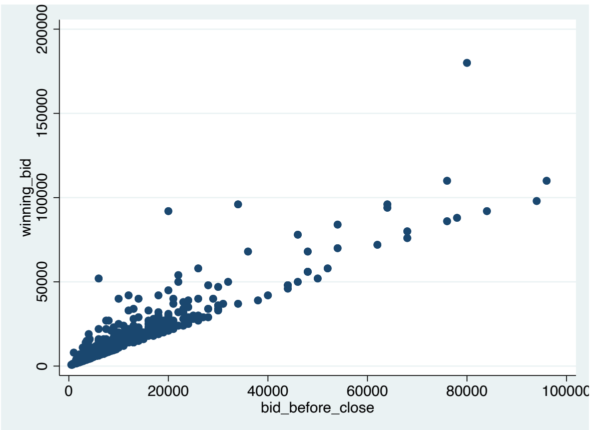
Distribution of total overtime length



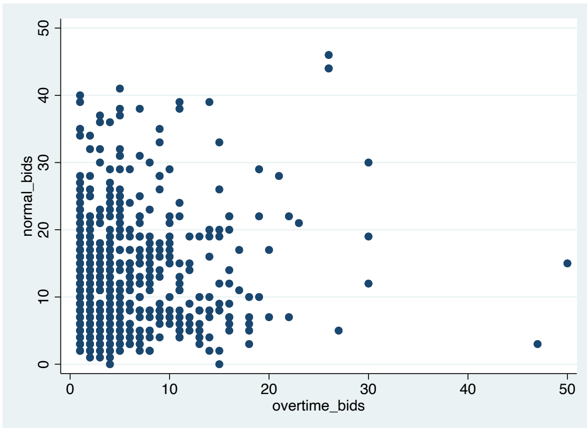
Distribution of total bids



Average expert score (By four experts)



Final price and the last bid before scheduled closing



Count of normal bids versus overtime bids

Source: Auction houses in participation

5 Empirical Analysis

5.1 Reduced Form Specification

Recognising the complexity of isolating bidding mechanisms, we complete our empirical analysis using a reduced-form regression framework. We examine how, for each item in an online art auction, the final price is determined based on item-level heterogeneity (item value) and the chosen bidding overtime policy (overtime effect).

In Section 3.3, the optimal overtime policy by countdown k for auction house profit aligns with the one for final prices. Since auction house profit is confidential, we reduce the model to emphasise the final price by collective effects of valuation learning (in Hypothesis 1) and attention cost (in Hypothesis 2), given the overtime duration policy k. The resulting equation is as follows:

$$P^* = \alpha_0 + \alpha_1 \Delta P_{learn}\big(EV_{i,0}(info(i)), k\big) + \alpha_2 \Delta P_{attention}(t^*(k)) + \varepsilon$$

We consider $info(i)$ as a transformation from the unobservable true item value V. To compare the impact of different bidding overtime strategies, we treat each observed overtime duration k as a dummy variable, where the coefficients associated show the magnitude of how final prices deviate from the baseline duration. After further eliminating the intermediate products and combining learning and attention, we have the following reduced-form specifications:

$$P^* = \beta_0 + \beta_1 V + \sum_i \beta_{i+1} k_i + \varepsilon$$

<u>Estimation of Item Level Heterogeneity</u>

As mentioned, the true value V of art and antiques is inherently uncertain and unobservable. Therefore, we incorporate expert scores and the normal bidding stage's bidding intensity as item value estimators in our model, which is standard practice when dealing with art valuations.

$$P^* = \widehat{\beta_0} + \sum_i \widehat{\beta_{i+1}} k_i + \varepsilon \qquad Setting\ 1$$

Setting 1 naively assumes that a larger sample size can dilute the effects of item-level heterogeneity and that an average item bundle under each overtime policy has the same V. This assumption is based on the idea that since all art auction houses here have access to similar auction items and audiences, and the auctions are conducted within a similar time frame, the socioeconomic environment remains relatively consistent across the sample.

$$P^* = \widehat{\beta_0} + \widehat{\beta_1} E[V] + \sum_i \widehat{\beta_{i+1}} k_i + \varepsilon \qquad Settings\ 2-6$$

Following that, we take a subjective approach by consulting domain experts, whose valuations may be good signals of an artwork's value (Beckert & Rössel, 2013). In practice, we invited four experts in the traditional Chinese arts industry to provide their expert score (0 to 9) based on their individual valuations and item recommendations for the sample set, corresponding to settings 2 to 5.

Furthermore, the normal period bidding intensity (an objective parameter calculated from data) is used as the item quality estimator in setting 6: the ratio of total normal period bids to total normal period bidders. This estimator is consistent with the intuition that auction items with higher bidding intensity are more competitive among buyers and, therefore, likely to have higher item values.

Overtime Policy Combinations and Subsets

As we acknowledge limited data availability in the 2-minute overtime policy, we merge 1-minute and 2-minute items into the "shorter duration" policy to enhance the robustness of the regression and, similarly, a "longer duration" policy for all other items.

To comprehensively understand and assess causal effects under varied conditions, we adopt the same regression techniques on specific subsets, such as higher final price items, expert selections (independently recommended items by domain experts), and specific categories (such as calligraphy).

5.2 Regression Outcome

Significance of Overtime Items

Before evaluating overtime policies, it is necessary to reiterate the importance of the items that trigger bidding overtime. Typically, items entering overtime have more bidders and intense competition, which results in a higher final price. Table 5.1 shows the significance of overtime items through three parameters:

Table 5.1: Coefficients On Overtime Parameters[1]

Variable	Overtime Items	Length of Overtime	Overtime Bids
Coefficient	7038.17**	11.40**	1212.18**
	(651.05)	(1.77)	(244.34)

An item with overtime, on average, produces a CNY 7000 higher final price than non-overtime items. Among items with overtime, a one-minute increase in the total overtime length also increases an item's final price by CNY 600. Thus, we confirm that items with overtime periods hold paramount significance for auction house profits.

<u>Optimal Overtime Policy</u>

We follow the six regression settings specified in Section 5.1. The outcome is given as follows:

Table 5.2: Regression of Overtime Dummy Variables

Regression Setup	$k = 120s$	$k \geq 180s$	$k = 180s$	$k = 300s$	$E[V]$
(1)	1316.35		6750.43**	5507.27**	/
Naïve	(1666.05)		(1721.53)	(1353.92)	
Assumption			6542.85**	5299.69**	/
			(1690.77)	(1315.24)	
		6005.27**			/
		(1207.82)			
(2)	-754.56		6161.70**	6962.73**	2158.66**
Overtime +	(1542.21)		(1626.95)	(1314.62)	(362.16)
Expert 1 Score			6281.48**	7076.37**	2152.18**
			(1611.09)	(1296.03)	(358.88)
		6619.73**			2133.15**
		(1186.22)			(361.56)
(3)	-1774.25		3329.72**	2938.13**	2607.63**
Overtime +	(1878.00)		(1500.61)	(1354.13)	(480.45)
Expert 2 Score			3640.47**	3239.90**	2580.10**
			(1480.92)	(1301.39)	(472.27)
		3462.40**			2585.04**
		(1080.40)			(478.03)

[1] The coefficient for overtime items is produced by regression on the entire dataset, while the sampled dataset produces the other coefficients. Length of overtime is defined in seconds.

Regression Setup	$k = 120s$	$k \geq 180s$	$k = 180s$	$k = 300s$	$E[V]$
(4)	-912.14		5247.53**	4700.04**	3611.19**
Overtime +	(1701.73)		(1576.13)	(1306.66)	(803.35)
Expert 3 Score			5396.91**	4846.07**	3593.82**
			(1561.43)	(1270.64)	(793.57)
		5156.48**			3603.26**
		(1114.15)			(799.66)
(5)	-4786.11*		3876.83**	4919.57**	3401.24**
Overtime +	(1935.30)		(1453.00)	(1294.43)	(611.45)
Expert 4 Score			4706.19**	5659.68**	3268.43**
			(1460.75)	(1269.90)	(583.94)
		5126.13**			3240.34**
		(1088.30)			(589.79)
(6)	711.52		5588.92**	7629.42**	4354.11**
Overtime +	(1593.88)		(1541.89)	(1323.36)	(756.73)
Normal Bidding			5473.88**	7520.01**	4361.67**
Intensity^			(1526.63)	(1305.57)	(755.11)
		6355.20**			4169.02**
		(1134.29)			(1840.13)

Notes: k=60s and k<180s are omitted variables used as benchmarks for each model specification. The results are coefficients and (robust standard errors).

A consistent pattern exists across all six setups, regardless of whether the regression uses naive overtime, expert scores, or normal bidding intensity. Aligned with our assumptions, all the $E[V]$s positively relate to the final price, confirming their effectiveness as item value estimators. The impacts of different overtime policies are also evident, with longer overtime durations ($k \geq 180s$) consistently associated with higher final prices, having the longer overtime effect ranging between CNY 3000 to CNY 7000, which may correspond to a 5-10 price level increase in overtime bidding.

In regression setups (1), (3) and (4), the 3-minute overtime duration stands out as the optimal policy, which leads to the highest final auction prices. We note that the difference in the 5-minute overtime coefficients is slight, and the price increase by 5-minute overtime is still significantly larger than the 1-minute and 2-minute overtime policies.

In regression setups (2), (5) and (6), the 5-minute overtime performs slightly better than the 3-minute overtime at the 1-2 price level, while the price increase is not as pronounced as over shorter overtime durations. This suggests that 3 minutes and 5 minutes perform equally well.

The difference between the 1-minute and 2-minute overtime policies does not appear to be statistically significant. This suggests that our current data are limited or that while longer overtime strategies can significantly impact the shortest overtime durations, they may not significantly impact final prices.

Higher Price & Higher Quality Items

We then examine the overtime effect over item quality, defined by higher-priced items and expert recommendations. To avoid multilinearity, $E[V]$ uses the averaged expert score on higher priced items and normal bidding intensity on expert-selected items. The observed patterns in Tables 5.3 and 5.4 show consistent patterns for both subsets.

Table 5.3: Regression for Items with Higher Final Prices

Regression Subset	$k \geq 180s$	$k = 180s$	$k = 300s$	$E[V]$ (expert score)
All Items		4215.79**	5311.84**	4375.90**
(667 Items)		(1456.64)	(1221.33)	(693.54)
	4701.19**			4337.87**
	(1053.23)			(698.20)
$P^* \geq ¥5000$		6692.71**	5143.20**	4154.96**
(471 Items)		(2026.40)	(1530.46)	(859.25)
	5953.68**			4228.03**
	(1433.77)			(867.80)
$P^* \geq ¥10000$		10230.06**	4557.24*	4822.01**
(265 Items)		(3152.50)	(2327.88)	(1275.76)
	7472.02**			5103.15**
	(2283.76)			(1299.85)

Notes: k<180s is omitted due to limited data in subset. k=60s is the omitted variable used as the benchmark for each subset regression. The results are coefficients and (robust standard errors).

The regression on higher priced items indirectly shows the existence of attention cost for Hypothesis 2. Higher-priced items require more bid increments, which would lengthen the auction and theoretically produce a large attention cost. Under the same $E[V]$, we observe that the overtime effect on the 3-minute policy is significantly higher in item prices above CNY 10000, while it is lower than the 5-minute overtime for all items data.

In the subset of expert-selected items, use the number of expert recommendations on a single item as an alternative item value indicator, denoted as $N[V]$, which is a positive indicator of V.

$$P^* = \widehat{\beta_0} + \widehat{\beta_1}E[V] + \widehat{\beta_2}N[V] + \sum_i \widehat{\beta_{i+2}}k_i + \varepsilon$$

Table 5.4: Regression for Expert Selected Items

Regression Subset	$k = 120s$	$k \geq 180s$	$k = 180s$	$k = 300s$	$N[V]$ (1 to 4)	$E[V]$ (intensity)
Expert	-4777.68		5934.68*	8152.11*	7951.20*	3999.55**
Selection	(3481.45)		(3439.64)	(4280.21)	(4060.16)	(1927.67)
(169 Items)			8183.26**	10457.3**	7730.15*	4067.41**
			(3564.55)	(4033.96)	(4026.14)	(1918.58)
		9014.57**			7824.15**	3841.56**
		(2938.44)			(3914.67)	(1874.24)

Notes: k=60s and k<180s are the omitted variables used as the benchmark for each subset regression. The results are coefficients and (robust standard errors).

Single Category Items: Calligraphy

Similarly, the subset which uses calligraphy items only suggests a similar observed pattern. The 3-minute overtime policy appears optimal in calligraphy as well.

Table 5.5: Regression for Calligraphy Category Items

Regression Subset	$k = 120s$	$k \geq 180s$	$k = 180s$	$k = 300s$	$E[V]$ (expert score)
Calligraphy	-850.18		9706.63**	9391.79**	3245.69**
Subset	(1955.96)		(2413.35)	(2988.75)	(849.56)
(158 Items)			9943.26**	9604.80**	3223.96**
			(2465.48)	(3028.99)	(840.66)
		9812.45**			3242.94**
		(1931.99)			(831.21)

Notes: k=60s and k<180s are the omitted variables used as the benchmark for each subset regression. The results are coefficients and (robust standard errors).

Indeed, longer overtime policies, including the 3-minute overtime duration, continue to outperform shorter overtime policies, with the 3-minute overtime having the highest price growth effect, at a CNY 9000+ difference compared to the 1-minute / 2-minute overtime. That confirms that the impact of overtime durations is not specific to certain art categories but can be universal in online art auctions if true item values are uncertain and unobservable.

5.3 Empirical Findings

Our empirical analysis reveals a clear pattern of overtime effects, particularly at shorter overtime durations, where we observe significant price increases at the 3-minute threshold. Considering Section 3.3, we observe that the optimal duration based on auction house profits should be slightly smaller than the optimal duration determined by the final price. Therefore, we recommend an optimal bidding overtime time of 3 minutes for art auction houses.

The price surge at longer overtime policies can be attributed to the "learning from price" mechanism. Bidders with uncertain valuations may build up their prices when the consideration time is sufficient. Our regression results show a 5-10 price level increase.

In contrast, transitioning from the 3-minute to 5-minute overtime shows a less pronounced effect. This might be the “attention cost” of increasing the auction length, which summarises the loss of enthusiasm, the opportunity cost of performing other tasks, or the need to participate in auctions for other items. This weak price drop in our data is 1-2 price levels.

In conclusion, our empirical findings would confidently and consistently support Hypothesis 1, indicating the prevalence of the valuation learning mechanism in shorter overtime durations for online art auctions, where the uncertainty condition applies. At the same time, while we do observe support for Hypothesis 2 in some settings, and through the relative difference in overtime effect via higher priced subsets, it appears to be a weaker influence. The offset by the attention cost mechanism remains relatively tiny, even in the 5-minute overtime duration, as total auction duration does not get excessively long.

6 Recommendations

6.1 Managerial Insights

We suggest a 3-minute overtime duration based on the theoretical model and our empirical findings on historical online auction data to our stakeholders and the art auction houses. The optimum of overtime is grounded by two fundamental mechanisms: the “learning in auction”, requiring a minimum time for bidders to learn and form valuations, and the “attention cost”, where long overtime durations disadvantage bidders through the opportunity cost in time. To keep the total auction duration reasonable while allowing bidders to achieve maximum valuations, we recommend that the art auction houses set the 3-minute strategy which shall maximise the total auction profit.

Apart from adjustments in bidding overtime configurations, there are multiple IT strategies to improve bidding dynamics through our proposed mechanisms: Auction houses shall consider implementing a strategic platform design that adapts to bidder behaviours: For instance, beautifying the application UI/UX to attract users and reduce the attention cost, highlighting the real-time bidding history and competition so that bidders can proactively learn from prices. These IT strategies can be used together with the optimal bidding overtime strategies to further increase the final price of items through bidding dynamics.

On the bidder side, or to counterfactually win the item at a lower price, if you want such an item, we provide the following bidding strategies: When the overtime strategy is long, you shall hold until the final closure, diminishing the interest of some potential buyers. For shorter overtimes, you shall bid as quickly as possible to reduce your opponent's decision-making time, thereby reducing their chance of learning and pushing the price higher.

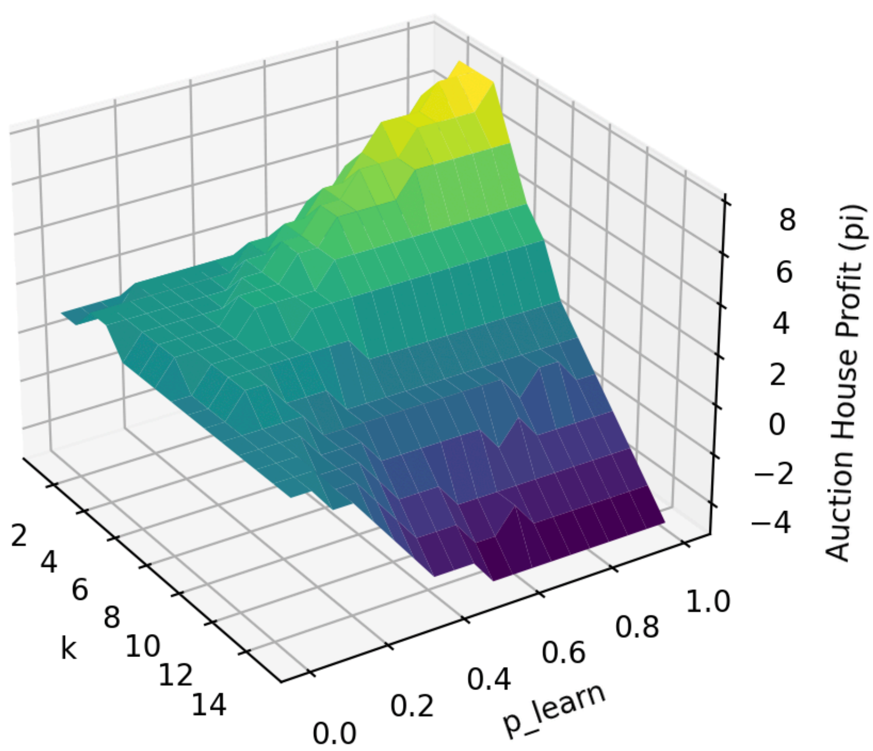
6.2 Application to E-Bay and Generic Online Auctions

For eBay or other lower-value auctions with deterministic valuations, "learning from prices" is weak since the assumption of unobservable item values, like in arts, does not hold. Thus, overtime shall have no impact on the final price. In these scenarios, bidders are fully aware of their valuations, which remain unchanged for the entire auction. Thus, the final prices shall remain consistent at the highest possible valuations throughout the bidding process.

Theoretically, we consider the difference between eBay auctions as a variation in the learning parameter p. As eBay auctions have mostly deterministic bidders, p tends to be small. We tune p to simulate changes in final profit through our auction model. Figure 6.1 uses Monte Carlo simulation to visualise the hyperplane of p, k and Π. Most eBay auctions would locate on the left part of the hyperplane, where k would have very little influence on the auction duration and final profits.

Moreover, eBay publishes an official guideline on auction sniping behaviour[2], as it does not have any overtime extensions, so sniping is available. While eBay mentions that bidders can turn on automatic bidding to avoid being snipped on their behalf, it does allow sniping behaviour. Given this, we assume snipping only affects the profits a little on eBay and other lower-value online auction sites, which aligns to our theoretical predictions.

Figure 6.1: Hyperplane of Learning, Overtime And Auction House Profit



6.3 Application to Physical Auctions

Physical auctions present a markedly different environment than the online art auctions of our study. Unlike online auctions, physical auctions give bidders a brief bidding window of 10-15 seconds to respond to previous bids, leaving no additional time to "learn." Similarly, the diminishing interest in items may not prevail in such a short period. Consequently, the "learning from prices" effect in online auctions may not exist in the fast-paced environment of physical auctions.

However, in traditional auction venues, bidders are physically present and can directly observe the behaviour of competitors. The nature of physical auctions encourages participants to

[2] eBay Help – Bid Sniping (https://www.ebay.com/help/buying/bidding/bid-sniping?id=4224)

scrutinise their opponents, interpreting their gestures, expressions, and activeness levels, among other physical “signals.” There can be some similar mechanisms of "learning from the room" at the start of the auction, especially for bidders with some experience. As a result, the on-site learning might favour experienced bidders, while newcomers are often at a disadvantage.

Still, numerous unidentified behavioural mechanisms would collectively shape the outcomes of physical auctions. For instance, as physical auctions have a shared audience and a large crowd, the noise from other items may influence auction outcomes, unlike online auctions where bidders have a single page for each item, making bidding dynamics entirely independent. It would be hard to research, though, as most auction houses in China keep their physical auction demographics confidential or do not record bidding history for physical items.

Thus, it would still be unclear whether physical auctions perform better than online auctions since the effects and mechanisms are systematically different. Another well-recognized effect particularly applicable to physical auctions is that when an auction gets longer, there is less interest in an item at a later position of the auction sequence (Reddy & Dass, 2006). Therefore, we suggest future laboratory experiments or targeted data collection to determine the empirical effect between the two venues.

7 Conclusions

7.1 Research Conclusions

In conclusion, this study focuses on bidding overtime, a key feature of online auctions to prevent auction snipping. It is a new feature of the Chinese art auction industry in its post-pandemic digital transformation. Apart from avoiding auction snipping, this study finds additional benefits of bidding overtime on facilitating bidding dynamics through a theoretical model and empirical analysis.

Through Monte Carlo simulation, we find out that there exists an optimal overtime duration that maximises auction house revenue. We propose two contrasting hypotheses: The valuation learning mechanism that pushes prices up when the overtime duration is longer and the attention cost that partially offsets the price increase.

Empirical analysis validates our hypotheses that longer overtime durations lead to higher final prices, and there are significant price jumps after a threshold of about 3 minutes. Furthermore, we see the price growth by increasing overtime durations weakens, representing the attention cost mechanism.

Based on our findings, we propose an optimal bidding overtime policy of about 3 minutes, which yields the highest profits in online art auctions. The price difference by overtime durations for eBay auctions is insignificant as bidders are deterministic. For physical auctions, the behavioural mechanisms can vary considerably. Therefore, this study lays the foundation for future art auction valuation and overtime optimisation research.

7.2 Limitations

While this research proposes and validates bidding mechanisms that lead to an optimal bidding overtime policy in online art auctions, certain limitations must be acknowledged. These limitations can be improved through further data collection and future research:

(1) The limited data and confidentiality concerns constrain the study.

While numerous online auctions happen daily, only very few items may enter the overtime bidding stage. Meanwhile, several auction houses in collaboration have limited IT technology levels, which makes data collection and processing particularly challenging. Furthermore, we cannot obtain further details about bidder characteristics due to policy restrictions. Therefore, we cannot study other potential mechanisms, such as influential buyers' entry or multi-item bidders' dynamics.

(2) Art auctions are highly subjective.

Despite the increasing digitisation and adoption of data analytics in the art auction industry, significant expert involvement is still required due to the uncertainty surrounding art valuations. Furthermore, it is difficult even for seasoned bidders to judge the actual "item value" numerically. Fakes and imitations may also appear in our items, confounding our empirical results.

(3) The research needs more overtime duration setups in the empirical data.

We cannot find desirable bidding data for most edge cases, such as very short (e.g., 30 seconds) or very long (e.g., 10 minutes) durations. In theory, testing these durations in controlled experiments would be possible, but this would be impractical given auction houses’ profit concerns.

(4) There may be auction house fixed effects.

Despite our efforts to mitigate this effect, such as filtering to a similar region, years of data, and auction house reputation, different auction houses may still result in a diverse audience pool, bidding practices, and item quality, which in turn affects final prices. This may reduce the generalizability of our results. Collaboration with multiple auction houses in a controlled environment, preferably under monopolistic competition, can further reduce the fixed effects.

(5) Bidder-level heterogeneity cannot be observed or removed.

Empirical data analysis cannot capture complex decision-making initiatives in dynamic environments. It is infeasible to isolate the micro-level mechanisms of online art auction participants. Controlled laboratory experiments may be ideal for quantitatively identifying these behavioural mechanisms.

Despite these challenges, further enhancements on the roles of bidding mechanisms in achieving optimal bidding overtime policies and the benefits to auction houses remains promising. Laboratory experiments and closer collaboration with auction houses may lead to more rigorous methods for validating our preliminary findings in future studies.

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The code package, including the code, public datasets, and detailed description of the package contents, is attached to the final submission. This project is also publicly available on GitHub (https://github.com/hytangs/IHT_Bidding-Overtime).

Optimal bidding overtime strategy for online art auctions:

Evidence from Chinese art auction houses