Data Preferences in Firm Learning: Evidence from an Online Auction Platform

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July 30, 2024

Job Market Paper

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Abstract

Governmental organizations and industry practitioners have promoted data sharing across firms to expedite learning to improve business decisions. However, current discussions have largely overlooked the possibility that firms may prefer their own data over others' data. This paper investigates the presence of such biased preferences among firms, focusing on used-car auction sellers on China's largest online auction platform. Auction timing is crucial on this platform as payoffs vary by hour, influenced by bidders' valuations and the number of residual bidders at different times. Despite being experienced local sellers before joining Ali Auction, these sellers face national demand and competition in the online environment, creating the scope for learning. Combining state-of-the-art auction literature, I develop a structural model of sellers' learning based on their own and others' data to optimize auction timing. The model estimates suggest that sellers' preferences for different data sources change with experience, with sellers weighing their own data at 90% compared to 10% for others' data at the average level of experience. Moreover, the data preferences account for more than half of the revenue gap between the status quo and the full information scenario. These findings have two implications for the platform. First, data sharing alone may not effectively guide sellers in selecting optimal auction timing. Second, the platform can leverage sellers' data preferences to guide new sellers to optimal timing early in their tenure, ensuring lasting benefits. Overall, the platform should play a coordinating role in helping sellers identify the best timing for their auctions.

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1 Introduction

Data have become increasingly important for business decision-making by enhancing firms' understanding of their customers and competitive landscapes. By comparing the performance of their past decisions in different market environments, firms can learn to adjust their decisions more effectively. Firms can rely on daily operations to generate their own data. However, the slow accumulation and limited scope of their own data can potentially lead to a prolonged learning process and, consequently, extended periods of suboptimal performance. Recognizing that data sharing across firms can expedite data accumulation and learning, the European Commission introduced the Data Governance Act, stating that "this [data] potential is not being realised... [Data sharing] has enormous potential to advance research and develop better products and services..." [1] The International Monetary Fund shares this opinion, arguing that data sharing can boost economic growth (Carriere-Swallow and Haksar, 2019). Meanwhile, new technologies such as privacy-maintained encryption have been developed to enable data sharing across firms, prompting the growth of the data-sharing industry, which has a market value of USD 15 billion in 2023 and is projected to reach USD 29.23 billion by 2030.[2]

While data sharing can rapidly increase the amount of data available to firms and potentially accelerate their learning processes, a crucial question remains: Do firms learn from others' data? Specifically, when both firms' own and others' data are accessible, do firms rely more on their own data in the learning processes? If firms value others' data the same as their own, they can benefit from the broader insights these additional datasets provide (Morris and Shin, 2002). Conversely, if firms have biased preferences toward their own data, the advantage of data sharing becomes less clear. In the extreme case, if firms disregard others' data entirely, increased data sharing will not expedite their learning. Therefore, understanding firms' preferences for their own data versus others' data is essential for illuminating the value of information provision and sharing.

This paper examines how sellers learn to choose optimal auction timing (i.e., the hour of the day) for their auctions on Ali Auction, the largest online auction platform in China, and quantifies the effects of the lack of information and sellers' preferences for their own data versus others' data.

[1] See: https://digital-strategy.ec.europa.eu/en/policies/data-governance-act-explained

[2] See: https://www.verifiedmarketresearch.com/product/b2b-data-exchange-market/#:~:text=B2B%20Data%20Exchange%20Market%20was,the%20forecast%20period%202024%2D2030.

Although these sellers were experienced local offline sellers before joining the platform, they need to learn how to choose the auction timing for their online auctions. Choosing the right auction timing is particularly important on Ali Auction due to the bidders' concentration in the last hour of the auctions and the different payoffs of the comparable auctions ending at different hours. I start by providing reduced-form evidence supporting that sellers learn to choose the auction timing and they have evolving preferences for their own data and others' data in their learning processes. To quantify the effect of the lack of information and data preferences using counterfactual experiments, I develop and estimate a structural model of sellers' ending hour choices, incorporating an adaptive learning process from both their own and others' data. Using the model estimates, I conduct counterfactual experiments by changing sellers' information environment and correcting their data preferences. The results show that data preferences play a main role in explaining the sellers' losses in expected revenue in their learning processes.

Ideally, to investigate how firms' own data and others' data affect their learning and decision-making, researchers would directly observe how different data sources shape firms' beliefs and how these beliefs subsequently affect their decisions. This data requirement poses two challenges in a field setting. First, firms typically do not record the beliefs that guide their decisions, let alone the beliefs formed from different sources of information. Consequently, researchers have to rely on the revealed-preference method, which infers firms' beliefs and their evolution from their actual decisions. Second, researchers need a context where firms' own data and others' data are clearly defined to examine how different sources of information translate into firms' actions.

I overcome these challenges by focusing on the used-car auctions on Ali Auction. As the largest online auction platform in China, Ali Auction features sellers that repeatedly engage with the platform and choose different timings for their auctions, enabling me to link their choices with changes in their beliefs. Moreover, the platform retains all historical records of auctions and provides automatic programming interfaces (APIs) for sellers to retrieve auction information. This setup allows sellers to access not only their own auction performance data but also those of other sellers. By collecting a unique and comprehensive dataset of all used-car auctions hosted on the platform since its inception, I can reconstruct each seller's own data and others' data at every choice occasion they face.

I restrict my sample to commercial auctions among all used-car auctions.[3] These auctions are hosted by commercial auction houses (i.e., sellers) on behalf of their clients to maximize the final transaction price of the cars. When hosting the auctions, these sellers have limited decision-making authority to avoid potential disputes if the auction does not conclude successfully. Decisions directly related to the auction payoff, such as the reserve price and minimum incremental bids, are typically left to their clients. The sellers primarily decide on the ending hours of the auctions. Although Ali Auction's stringent eligibility requirements restrict these sellers to being experienced local offline sellers before joining the platform, Ali Auction exposes them to national demand and competition, necessitating learning how to select optimal ending hours.

I first establish that the ending hours of auctions matter on this platform. Although bidders can enter an auction at any time, I find that most bidding occurs in the last hour of the auctions in the sample, consistent with evidence from other online auction platforms (Roth and Ockenfels, 2002).[4] I categorize the cars into five tiers based on the sellers' valuation of the cars. I show that within the same tier of cars, different ending hours yield different payoffs for the sellers, after controlling for heterogeneities in auctions and sellers. For example, the most expensive cars have the highest expected payoffs around 1 PM, while the least expensive cars have the best outcomes around 6 PM. These findings suggest that choosing different ending hours can significantly affect sellers' payoffs for the same car.

I then present reduced-form evidence indicating that sellers engage in learning to optimize their decisions regarding auction ending hours. Specifically, I document that sellers narrow their ending hour choices to a few higher-payoff ending hours. During this transition process, sellers gradually abandon the commonly chosen and worst-performing hours. As a result of their learning, the payoffs of the auctions, conditional on selling, improve over time.

To investigate how sellers utilize different sources of information available to them on the platform, I examine how they respond to the unexpected payoffs from their own data and others' data. When there is a positive unexpected payoff for their auctions at the current ending hours, regard-

[3]My data also include other subcategories of auctions defined by the identity of the sellers, such as judicial auctions hosted by local courts and bankruptcy auctions hosted by banks or liquidators.

[4]Ali Auction does not have fixed deadlines for auctions. Instead, if a bidder places a bid in the last five minutes of an auction, the auction's deadline is automatically extended for another five minutes. Although Roth and Ockenfels (2002) predict that auctions with flexible deadlines will be less prone to last-minute bidding, the ranking algorithm on Ali Auction ranks near-closing auctions at the front, leading to last-minute bidding, a prediction also discussed in (Roth and Ockenfels, 2002).

less of the source of information, sellers are less likely to change the current ending hours. This suggests that sellers incorporate both sources of information in their decision-making. However, I find that sellers gradually rely more on their own data than on others' data. This indicates an evolving preference for these two sources of data that changes with their experience. While unboxing the underlying mechanisms would require more detailed data to delve into the black box of sellers' learning processes, I discuss that this result is consistent with the findings in behavioral economics literature, suggesting that effort in generating data (Conlon et al., 2022b), ownership effect (Hartzmark et al., 2021), or broadly rational inattention (Maćkowiak et al., 2023) may play a role.

To conduct counterfactual experiments to quantify the effect of limited information and data preferences in sellers' learning processes, I develop a structural model in which sellers decide on the ending hours to maximize the expected payoffs for each auction. I first adapt Freyberger and Larsen (2022)'s framework to recover the bidders' valuation distribution for each hour. I then assume sellers follow an adaptive learning process to form expectations about the arrival processes of residual bidders using their own data and others' data, respectively. For each data source's predicted number of bidders, the sellers take into account the bidders' valuation distributions and form the expected payoffs. I assume that the sellers maximize the weighted average of the expected payoffs from their own data and others' data, with the weights capturing their experience-evolving preferences for these two sources of data.

The particular interest in the estimated parameters lies in how sellers weigh their own data versus others' data. The estimated coefficients imply that sellers place a small weight on others' data overall. When sellers have little experience, they rely on others' data. However, this preference quickly changes as they start accumulating experience. At 30 auctions, sellers weigh the two sources of information equally. At the mean level of experience (272 auctions), sellers weigh their own data at 90% and others' data at about 10%.

To inform the platform about the information-sharing policies, I examine whether the main driver behind sellers' suboptimal decisions in their learning processes is the lack of information or a preference for their own data. I first compare the status quo with an ideal full-information scenario. In the status quo, the sellers make suboptimal decisions due to two factors: limited information and a biased preference for their own data. In contrast, under the full-information scenario, sellers' revenue would increase by 6.4%.

To examine which factor is the main driver, I conduct decomposition exercises by sequentially providing information to the sellers and correcting their data preferences. Since the sequence of these corrections may affect the results, I perform two exercises, each with a different order of corrections. In the first exercise, I first provide the sellers with the information and then correct their data preferences. In the second exercise, I reverse this order, correcting their data preferences before providing the information. Both exercises indicate that data preferences account for the majority of the revenue gap, explaining up to 61% of the revenue gap between the status quo and the full information case.

Overall, the results have two key implications for the platform. First, as the counterfactual results suggest, data preferences may hinder sellers from fully utilizing shared data. The platform should consider sellers' data preferences when determining whether data sharing is an effective strategy to help sellers improve their auction timing choices. Second, the platform can leverage sellers' preferences for their own data by guiding them to better time slots during their early stages on the platform. This will have long-lasting effects, as the sellers will later heavily rely on their own auctions' performance to decide on ending hours. Together, the platform can consider a coordination role by charging different service fees for different ending hours to guide sellers' decisions or by using ranking algorithms.[5]

Related literature. The main findings of this paper contribute to our understanding of how firms use others' data and inform the policy initiatives on data sharing. Current studies examining how firms use others' data largely focus on instances where firms purchase data from brokers. For example, in marketing, Neumann et al. (2019) study the effectiveness of ads targeting based on data sold by brokers to marketers. They find that consumer segments defined by data brokers are often inaccurate. In a follow-up paper, Neumann et al. (2023) compare the effectiveness of firms' own data to data bought from brokers and find that firms' own data are more effective in identifying the right consumer groups. In finance, Jappelli and Pagano (2002) and Djankov et al. (2007) study data sharing among financial institutions via credit bureaus (i.e., data brokers) find

[5] Ali Auction currently charges a service fee for each successful auction on the platform and displays the auctions based on the ending hours for all the bidders.

that the data sharing allows banks to extend more credit while suffering fewer defaults. While previous papers focus on the role of shared data by data brokers, a recent paper by Wu et al. (2023) studies how a platform should design data sharing with sellers to facilitate price targeting in equilibrium. In this paper, I focus on how firms leverage shared data in their learning process to understand the market environment. The results illustrate that data sharing might be effective when firms' own data are limited, as firms primarily rely on shared information, conceptually consistent with the predictions from Pagano and Jappelli (1993) and findings in Wu et al. (2023). I additionally show that when firms have accumulated their own data, the benefits of shared data diminish. This finding suggests that policy initiatives on data sharing may primarily benefit firms with little experience by jumpstarting their learning, but the effect on more established firms may not be as significant.

Another contribution of this paper is to the literature on social learning. At the individual level, existing research has examined how factors such as gender (BenYishay et al., 2020), social status (Gong et al., 2022), and differences in decision-making power (Conlon et al., 2022a) influence individuals' preferences for information sources. Several papers using lab experiments further establish that individuals respond differently to various sources of information. Conlon et al. (2022b) find that individuals prefer their own data because they have exerted effort, even when it is equivalent to others' data. Hartzmark et al. (2021) show that ownership leads individuals to prefer signals from their own goods. Jamison et al. (2017) find that consumers' adoption of new green technology accelerates if they observe others' decisions, but they rely on private signals once they adopt. At the firm level, papers have looked at how firms in different industries incorporate others' information through learning spillovers (e.g., oil: Covert 2015; Hodgson 2021; solar panels: Bollinger and Gillingham 2019; IT: Cheng et al. 2021). The literature has found mixed evidence. While some studies indicate the presence of social learning (e.g., Covert 2015; Hodgson 2021; Cheng et al. 2021), others show minimal or no social learning (e.g., Bollinger and Gillingham 2019). This paper adds to the literature by providing additional empirical evidence that sellers incorporate different information sources in their decision-making. The finding that firms overweight their own data in the learning process is similar to that in Covert (2015) and Hodgson (2021). Yet, different from Covert (2015) and Hodgson (2021), I highlight the evolving nature of firms' preferences for their own and others' data in their learning process as they gain experience.

Broadly, this paper also relates to recent research in economics and marketing that examines how firms learn to improve their business decisions. While empirical studies in social learning have largely focused on R&D decisions by analyzing learning spillovers, some recent papers have looked at how firms learn to price (Huang et al., 2022; Doraszelski et al., 2018; Huang et al., 2019), invest (Jeon, 2022), place advertisements (Mela et al., 2024), and rate loans (Li and Ching, 2023). While these papers focus on how firms learn from their own information, I study how firms learn to make entry decisions by combining different sources of information and how they use these data.

Moreover, as the empirical setting of this paper is an online auction platform, this paper contributes to the empirical auction literature by analyzing sellers' strategic behaviors regarding auction timing. Previous research in auctions has largely focused on sellers' choices of auction formats (such as auction versus fixed-price) or designs (such as reserve prices). For a recent review, see Hortaçsu and Perrigne (2021), and Ockenfels et al. (2006) also provide an overview of online auctions. Closely related is Marra (2024), who also investigates sellers' auction listing decisions. While Marra (2024) focuses on the selective entry of sellers on the platform due to network effects and the consequences of the platform's fee structure, I focus on the sellers' learning process in deciding when to list their auctions.

Roadmap. The rest of the paper is organized as follows. Sections 2 and 3 introduce the empirical context and data, respectively. Section 4 documents descriptive evidence regarding sellers' learning about ending hour choices. Section 5 outlines the structural model that I use to recover the bidders' valuations, and Section 6 presents a structural model of sellers' choices on auction timing with learning. Section 7 shows the results of the structural model estimation. Section 8 discusses counterfactual experiments. Lastly, Section 9 concludes.

2 Empirical Context

2.1 Ali Auction and Commercial Used-Car Auctions

I focus on Ali Auction, the largest online auction platform in China, as the empirical context for this paper.[6] Ali Auction hosts various types of auctions, classified into different categories based on two criteria: the auctioned objects' categories, such as automobiles and real estate, and the ownership of the assets, such as commercial, judicial, or state-owned enterprises.[7] In 2018, the annual transaction value on the platform exceeded CNY 500 billion (approximately USD 70 billion).[8]

In this paper, I focus on commercial used-car auctions. These auctions involve vehicles previously owned by companies seeking to replace or dispose of their cars. While these companies cannot directly host auctions on the platform, they must commission an eligible auction house (henceforth, sellers) to host the auctions on their behalf. In this process, sellers charge a percentage of the final transaction value as their commission fee.

Ali Auction imposes stringent requirements on the eligibility of these sellers. They must meet capital and staff requirements, have experience in the auction industry, and possess all the licenses required by regulatory agencies and the government.[9] In other words, these sellers are experienced auction houses adept at managing auctions.

Although experienced in running auctions, prior to Ali Auction, these sellers primarily operated locally. Similar to other online auction platforms, the key benefit of Ali Auction is the access it provides to the national market.[10] When these sellers first joined Ali Auction, they started facing national demand and competition, which differed from the local environment they were used to.

[6]See: https://tech.sina.cn/i/gn/2014-08-12/detail-iawzunex3495288.d.html. Accessed on March 1, 2024; in Chinese.

[7]These categories include commercial assets, litigation-involved (judicial) assets, state-owned enterprise assets, investigation-involved assets, government assets, financial assets, and bankruptcy assets. For example, in used-car auctions, commercial assets are cars owned by companies, litigation-involved assets are cars temporarily owned by local courts, and state-owned enterprise assets include cars owned by state-owned enterprises. Investigation-involved assets are cars confiscated by police departments, government assets are cars previously owned by local governments, financial assets are cars owned by debtors, and bankruptcy assets are usually owned by banks or insurance companies.

[8]Source: https://finance.sina.cn/usstock/mggd/2019-06-30/detail-ihytcerm0365383.d.html?from=wap. Accessed on May 20, 2024; in Chinese.

[9]These criteria include a minimum registered capital of CNY 1 million, having auction licenses and certificates from local regulatory agencies, a minimum of one year of experience in the auction industry, and a minimum of five staff members. Source: https://help-paimai.taobao.com/page/knowledge?pageId=198&category=1000033658&knowledge=1060254624&language=zh. Accessed on May 15, 2024; in Chinese.

[10]See: https://baijiahao.baidu.com/s?id=1786323329205312316&wfr=spider&for=pc. Accessed on March 20, 2024; in Chinese. The first quoted reason is to increase the "potential demand."

This created uncertainties in the decision-making process and the need for learning.

On the bidder side of the platform, Ali Auction has a group of ordinary individual customers who bid in auctions. Although the platform does not exclude professional buyers, such as used-car dealers, it does not have a significant portion of repeated buyers who regularly engage with the markets (Guan and Xu, 2024).

2.2 Auction Process on Ali Auction

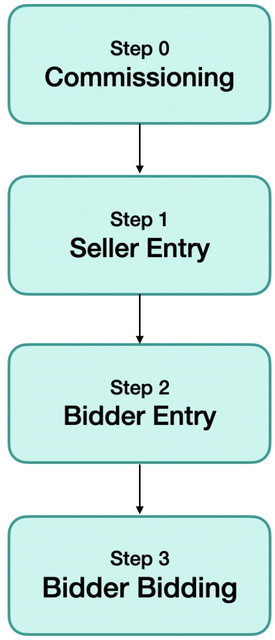
As introduced in the above subsection, an auction begins with a client commissioning an auction house (i.e., seller) to host the auction on their behalf (Step 0 in Figure 1). During the commissioning process, the clients decide on the date of the auction, starting price, reserve price, participation deposit, and minimum incremental bids. Except for the date, all other variables are directly related to the eventual monetary returns of the auctions. The sellers will only advise their clients if needed to avoid potential responsibilities if the auction outcomes do not meet their clients' expectations. Ali Auction also requires a detailed description of the cars in a standardized format, usually provided by the clients to the sellers.[11]

Once the client commissions a seller, the seller will make an entry decision by deciding on the starting hour of the auction given the chosen date by the client (Step 1 in Figure1). Since these auctions usually last for 24 hours, the decision is equivalent to choosing the ending hours for the auctions. Then, the seller will release an announcement about the upcoming auction, detailing the time and other auction-related information (as discussed in Step 0). These announcements are typically released five to seven days before the start of the auctions to allow bidders to enter.

When bidders arrive at the platform, they see the announcements and decide which auction to participate in (Step 2 in Figure 1). To bid in an auction, bidders must pay a participation deposit to become eligible. The platform freezes the deposit in the bidders' account and will only unfreeze the money one week after the auction concludes. The deposit can be used as part of the final payment if the bidder wins. If the winning bidder defaults on the winning bid, the seller will collect the deposit. In other words, this deposit represents the minimal value that the sellers and their clients

[11]For the requirements of the description of the cars, see https://help-paimai.taobao.com/page/knowledge?pageId=198&category=1000033654&knowledge=1060862835&language=zh. Accessed on May 15, 2024; in Chinese. The Ministry of Commerce of the People's Republic of China also published the requirements for information disclosure of automobile auctions in 2012 and the updated version in 2018.

Figure 1: Flowchart of An Auction's Process



Notes: This figure shows the flow of an auction on Ali Auction. In the first step, a company (i.e., a client) that is looking to dispose of their cars through Ali Auction will find a seller to host the auction on their behalf. The client will decide on the eventual payoff-relevant variables. Once the seller is commissioned, the seller will make an entry decision by deciding on the hour of the auction. Then, the interested bidders pay the participation deposit (Step 2) and bid in the last step.

can collect from a successfully sold auction item.

Next, the bidders who have paid the participation deposit will bid in an ascending English auction with an open reserve price. The first bidder must submit a bid higher than the starting price, and subsequent bidders can submit any bids higher than the previous one, subject to the minimum incremental amount. In this process, bidders cannot use automatic bidding; they must submit their bids manually. Ali Auction does not impose a hard deadline on the auctions. If someone bids in the last five minutes, the auction is automatically extended for another five minutes. The auction concludes when no one bids in the extended five minutes, and the highest bidder wins the auction.

2.3 Information Environment on Ali Auctions

Ali Auction maintains a transparent information environment and does not delete any past auction information. While sellers can directly observe their own auctions' performance, Ali Auction provides easy access to other sellers' auction data. Like many other digital platforms, Ali Auction offers automatic programming interfaces (APIs) that sellers can use to retrieve other sellers' auction performance data.[12] The retrieved others' data include other sellers' car details, the number of potential bidders, and the outcomes of these auctions. While sellers can use other tools for information collection, the APIs provide a seamless way to access others' data.

3 Data

I collect a novel and comprehensive dataset of all used-car auctions on Ali Auction from its launch in 2012 to June 2022. The dataset includes 438,273 auctions from 6,532 sellers over the past ten years. I first describe my dataset and then discuss my sample construction for the analyses.

3.1 Datasets

I collect three datasets regarding the used-car auctions on Ali Auction: auction announcements, auction-level information, and bidding records.

Auction announcements. For each auction, I first collect the corresponding announcements that the sellers publish. This includes the seller ID, the unique auction ID, the announcement publishing time, the auction's planned starting and ending hours, and the number of images of the vehicles. The announcements also specify the starting price, reserve price, minimum incremental bids, and participation deposit. Additionally, I collect the car characteristics from the announcements, including descriptions of the vehicles' conditions.

Auction-level information. In addition to the information contained in the announcements, I collect the auction outcomes, including whether the car is successfully sold and, if so, the winning bid. I also record the number of potential bidders, defined as those who have paid the participation deposits.

[12]For Ali Auction, the APIs are accessible through https://developer.alibaba.com/docs/api.htm?spm=a219a.7395905.0.0.28bb75feJfZBHT&apiId=26172. Many other digital platforms also provide APIs for their users to retrieve information, such as TikTok (https://developers.tiktok.com/doc/overview/) and Twitch (https://dev.twitch.tv/docs/api/reference/).

Bidding record. To supplement the auction-level information, I also collect comprehensive bidding records for all the auctions in the dataset. I observe the unique bidder IDs, the timestamp for each bid, and the amount for each bid.

3.2 Sample Construction

The focal samples used in the analyses are from the commercial auctions as described in Section 2.1. This results in a dataset of 93,125 auctions that were completed, regardless of whether the auction resulted in a successful sale.[13] Although this refined sample comprises only 27% of the overall data, it represents the largest category in which Ali Auction generates revenue in the used-car segment, accounting for 62% of the total number of auctions among these categories.[14]

To reduce the computational burden, I further limit the sample period to 2020-2022, a period during which used-car auctions showed substantial growth.[15] I restrict the focal auctions to those that started between 9 AM and 10 PM, the most active hours on the platform as shown in Figure A.1. This leaves me with 87,054 auctions from 543 sellers. I use all 87,054 auctions to recover bidders' valuations.

For the main analyses of firms' learning and their use of information, I focus on the largest sellers on the platform, defined as those having more than 500 auctions during the sample period. This set of sellers includes a total of 35 firms. However, the largest seller in the sample was banned by the platform for undisclosed reasons. As these bans are often due to violations in conducting auctions, I drop the auctions from this seller.[16] To facilitate the structural analyses, I further exclude two firms due to their use of simple heuristics in deciding the ending hours (i.e., spreading all the auctions over all the time slots).[17] I provide further rationale and details for this adjustment in Appendix A. As a result, I focus on 32 sellers and their decisions on 47,472 auctions when

[13] This excludes auctions that were retracted, which usually occur due to errors in the announcements. Since Ali Auction requires announcements to be accurate and precise, any errors lead to retractions.

[14] A detailed distribution of the number of auctions for each ownership category and the corresponding shares is included in Table A.1. Judicial auctions are the largest category by volume. However, Ali Auction does not charge any fees for these auctions, viewing this as part of their social responsibilities.

[15] See https://www.sohu.com/a/719977357_121040187. Accessed on May 15, 2024; in Chinese.

[16] For such regulations from Ali Auction, see https://www.taobao.com/markets/paimai/jghelp?path=paimaiguize. Accessed on May 1, 2024; in Chinese.

[17] This simple heuristic may reflect sellers' heterogeneous ability in learning. While the current seller model considered in Section 6 assumes homogeneous learning behavior while allowing for heterogeneous beliefs, learning models that capture the hierarchy in firms' learning processes, such as Cognitive Hierarchy (Cramerer et al., 2004; Goldfarb and Xiao, 2011) or Level-k learning (Costa-Gomes and Crawford, 2006; Crawford and Iriberri, 2007), can be used to capture the simple heuristics. I plan to explore this further in the future.

examining their learning and choices for ending hours.

The details of sample construction can be found in Appendix A.

3.3 Summary Statistics

The summary statistics presented in Table 1 offer an overview of both seller-level and auction-level activities on Ali Auction.

Panel A of Table 1 focuses on seller-level metrics, highlighting significant variability in the number of auctions conducted by each seller. The mean number of auctions per seller is 160.32, with a substantial standard deviation of 697.63, indicating a wide range of auction activity among sellers. The distribution is right-skewed, as evidenced by the 25th percentile at 2 auctions and the 75th percentile at 40.5 auctions. This suggests that while some sellers are highly active, many conduct relatively few auctions. Annually, sellers hold an average of 114.39 auctions, with a standard deviation of 519.61, further emphasizing the diversity in seller engagement. The median number of auctions per year is 8, with the interquartile range spanning from 1 to 33 auctions.

Panel B provides detailed auction-level statistics, focusing on auctions' payoff-relevant variables and performance. The variables, except for the sale indicator, are winsorized at the 1% level to reduce the impact of outliers. The average deposit amount is \$1,278.40, with a standard deviation of \$1,129.95, reflecting notable variation in deposit values. Reserve prices exhibit even greater variability, with a mean of \$7,852.36 and a standard deviation of \$13,597.80. The large variations in the participation deposits and reserve prices reflect the heterogeneity in the cars auctioned on the platform. The minimum incremental bid percentage averages 5.41%, with a standard deviation of 6.09% of the reserve prices. Overall, the magnitudes of the minimal incremental bids are small compared to the reserve prices. Auction durations are relatively consistent, with a mean of 24.55 hours and a standard deviation of 0.77 hours, reflecting the platform's typical 24-hour auction cycle.

Regarding auctions' performance, the number of interested bidders per auction, defined as those who have paid the participation deposits, averages 6.12, with a standard deviation of 5.81. The median number of bidders is 6, with the 25th percentile at 0 and the 75th percentile at 10. Overall, this suggests that while a smaller portion of the auctions do not attract any bidders, the majority of the auctions are popular. The indicator variable $\mathbb{I}(\text{Sold})$ shows that 64% of auctions result in a sale. The average winning bid amount across all auctions is $7,221.06, with a standard deviation of $9,861.73, and a median of $4,198.57. For auctions that successfully sold items, the average winning bid increases to $11,239.7, with a standard deviation of $10,305.8, and a median of $8,671.43. These statistics underscore the substantial variation in auction outcomes.

Table 1: Summary Statistics

	N	Mean	SD	Q25	Median	Q75
			Panel A: Seller Level			
No. of Auctions	543	160.32	697.63	2.0	9.0	40.5
No. of Auctions Per Year	761	114.39	519.61	1.0	8.0	33.0
			Panel B: Auction Level			
Deposits ($)	87,054	1,278.4	1,129.95	714.289	857.14	1,428.57
Reserve Price ($)	87,054	7,852.36	13,597.8	857.143	1,428.57	8,928.57
Minimum Incremental Bids (%)	87,054	5.41	6.09	0.70	4	7.50
Duration (Hours)	87,054	24.55	0.77	24.00	24.24	24.77
No. of Bidders (Interested)	87,054	6.12	5.81	0	6	10
$\mathbb{I}$(Sold)	87,054	0.64	0.479	0	1	1
Winning Bids ($)	87,054	7,221.06	9,861.73	0.0	4,198.57	10,457.3
Winning Bids(cond., $)	55,929	11,239.7	10,305.8	4,571.57	8,671.43	13,714.1

Notes: Panel A shows the summary statistics at the seller level. *No. of Auctions Per Year* is at the seller-year level. Panel B shows the summary statistics at the auction level. $\mathbb{I}(Sold)$ is an indicator of whether the auctioned item has been successfully sold. All variables, except for the indicator for being successfully sold, are winsorized at the 1% level to remove the impact of the outliers.

4 Descriptive Analysis

As used cars are highly idiosyncratic, I first discuss how I cluster the auctioned cars in these auctions. Then, I proceed to present descriptive evidence that the hours of the day matter on the auction platform, that sellers learn to improve their auction ending hour decisions, and how firms use different sources of information in their learning processes.

4.1 Clustering of the Used Cars

Used cars can be highly differentiated due to their idiosyncratic characteristics. Unlike new cars, which share a common set of characteristics up to aggregation, used cars of the same brand, model, and make can differ significantly due to previous owners' usage, including factors like mileage, paint, cleanliness, or overall condition. While one could view each car as a unique product, this approach is not practical in the used-car market and imposes computational challenges in the later analyses.[18]

To facilitate the analyses, I cluster the cars based on the effective reserve price, defined as the maximum between the participation deposit and the reserve price of the auctions set by the auction houses. As discussed in Section 2.2, the participation deposit represents what the sellers and their client firms can recover if the winning bidder reneges on the bid. Due to the complementarity between participation and reserve prices, as pointed out in Che et al. (2022), I take the maximum of the two as the effective reserve price and assume it provides sufficient summary statistics of the underlying value of the cars that the auction houses and their clients place on the vehicles. I implicitly assume a non-decreasing relationship between the unobserved characteristics of the cars and the effective reserve price, similar to the assumption in Roberts (2013).[19] I then divide the sample of auctions into five tiers based on effective reserve prices, with the first tier being the best and the fifth tier being the worst.[20]

4.2 Ending Hours Matter on the Platform

To motivate the sellers' strategic decisions on ending hours, I first document that the majority of the bidding occurs in the final hours of the auctions. Then, I show that similar auctions scheduled to end at different hours yield different payoffs. These two pieces of evidence underscore the importance of sellers choosing the right ending hours for their auctions.

4.2.1 Biddings concentrate in the last hour of the auctions

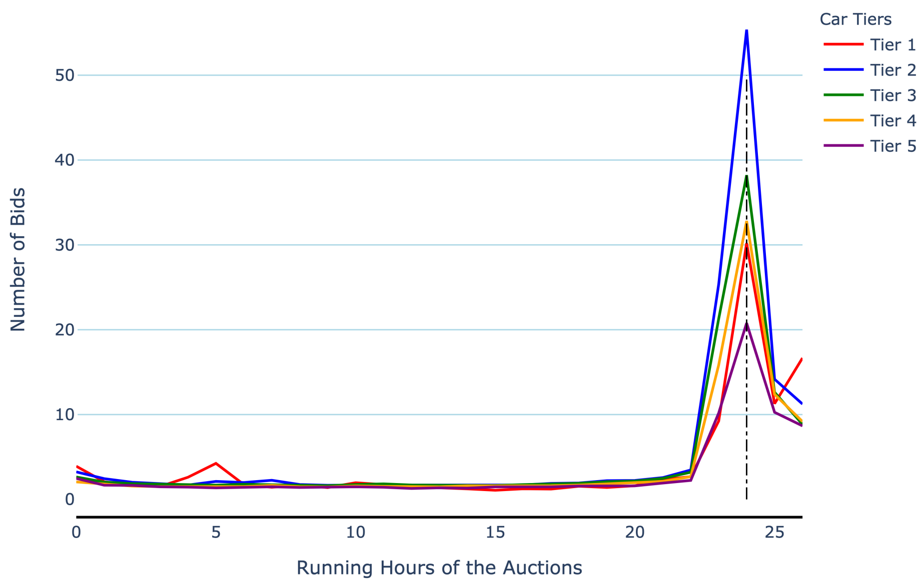
I first document that the majority of the bids are concentrated in the last hour of the auctions. Figure 2 illustrates the inter-temporal distribution of bids over the running time of auctions, segmented by car tiers. The plot shows the changes over the course of 26 hours to accommodate the potential extensions due to bids in the last five minutes. Different vehicle tiers are labeled using different colors, and the black vertical dashed line indicates the typical 24-hour running time of an auction.

[18]Used car markets usually categorize cars based on price and other characteristics, such as models and makes. For example, on Carvana, one of the leading online used car dealers in the US, cars are divided by price range, models, makes, years/mileage, etc.

[19]Note that this is only in principle similar to the assumption in Roberts (2013). In the structural analyses, I explicitly control for the distribution of the unobserved heterogeneity but allow the sellers to have private valuations within each tier.

[20]The value of the cars is commonly used in the Chinese used-car market. For example, on Ali Auctions, this is included as one of the top characteristics displayed in the summary information of the auctions.

Figure 2: Distribution of the Bids Over the Running Time of Auctions



Notes: This figure shows the inter-temporal distribution over the running time of auctions. Different tiers are labeled using different colors. The x-axis is the running time of the auctions and the y-axis is the number of bids. Note that this may be different from the actual number of bidders because the bidders can submit multiple bids. The black vertical dashed line marks the 24 hours of the auctions.

Two features of the plots stand out. First, the majority of bids are concentrated toward the end of the auction period. Specifically, the number of bids significantly increases during the last hour, with a peak observed right before the auction closes. Second, this trend is consistent across all car tiers, indicating that bidders, regardless of the car tier, prefer to place their bids towards the auction's conclusion. This behavior suggests that optimizing the ending hours of auctions could be crucial for maximizing participation and competitive bidding.[21]

[21] This feature is not unique to Ali Auction. Previous papers have documented a similar phenomenon on other auction platforms, particularly those with hard deadlines like eBay (Roth and Ockenfels, 2002; Ariely et al., 2005), and termed this particular bidding behavior as "sniping" (Hortaçsu and Bajari, 2003; Roth and Ockenfels, 2002; Ariely et al., 2005). As introduced in the previous section, Ali Auction does not have a hard deadline. Instead, each auction's deadline will be automatically extended, similar to Amazon Auctions studied in the literature (Roth and Ockenfels, 2002; Ariely et al., 2005). Although Roth and Ockenfels (2002) argue that auction platforms with flexible deadlines are less likely to experience sniping, Ali Auction displays near-ending auctions first on their page. This is consistent with Roth and Ockenfels (2002)'s further explanation that non-strategic considerations from the bidder side, such as platform recommendations of near-ending auctions, can induce such behavior.

4.2.2 Payoffs vary by ending hours for similar cars

To investigate how different ending hours affect auction payoffs, I run the following fixed-effect regression for each tier of cars ($k = \{1, \cdots, 5\}$) using the auctions a in tier k:

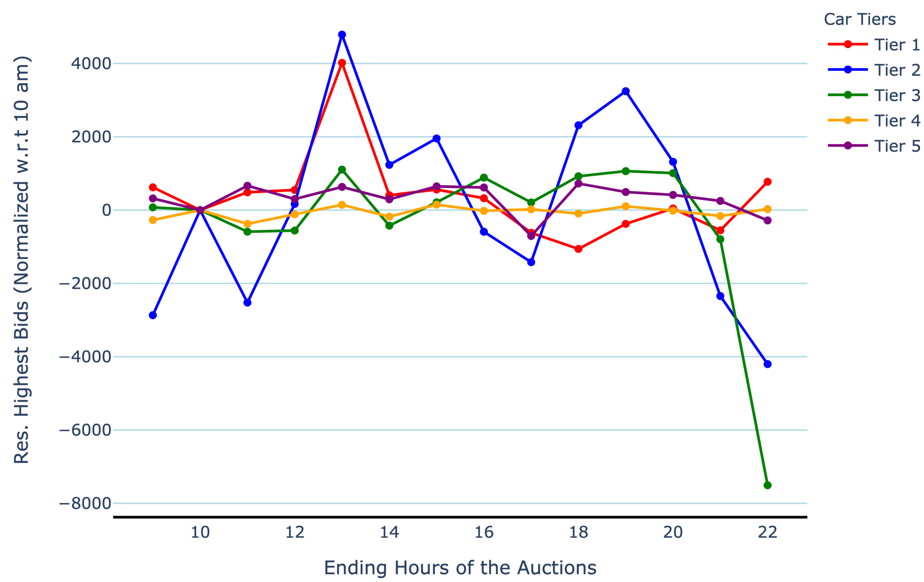
$$\text{Highest Bid}_{a(k)t} = \alpha_t + \beta * \text{Auction Controls} + FE_{y(a)\times m(a)} + FE_{dow(a)} + FE_{s(a)} + \epsilon_{a(k)t} \quad (1)$$

Equation 1 compares the highest bids for auctions with different ending hours in a given tier k, captured by α_t. The variable Auction Controls includes the characteristics of the auctions.[22] Additionally, to account for the seasonality of the market, I include flexible time-fixed effects through the interaction between the year and the month of the auction ($FE_{y(a)\times m(a)}$). To address potential day-of-the-week effects, I add the day-of-the-week fixed effects, $FE_{dow(a)}$. I also control for the seller-specific fixed effects, $FE_{s(a)}$.

Figure 3 presents the estimated α_t from Equation 1, normalized with respect to 10 AM, for different car tiers. Two observations can be made from the figure. First, within each tier, there is substantial variability in the intra-day payoffs, indicating that the timing of auction closures significantly impacts auction outcomes. For example, Tier 1 cars (red line) show a single peak at 1 PM, with all other periods yielding lower payoffs. In the morning to early afternoon periods, the payoffs gradually increase, peaking at 1 PM, then gradually decreasing until 6 PM. However, payoffs increase again in the evening, reaching another smaller peak at 10 PM. For Tier 3 (green line), the payoffs show relatively smaller variations before 8 PM but change drastically after that. Second, different tiers of auctions exhibit different intra-day patterns. For example, for more expensive cars (Tiers 1 and 2), 1 PM shows the highest peak, while for the least expensive cars (Tier 5), 6 PM is the best time. These patterns highlight the importance of strategic decision-making regarding auction ending hours to maximize payoffs.

[22] Specifically, it includes factors such as the number of images, effective reserve price, previous auction attempts, mortgage assistance availability, state-owned-enterprise status, and secured-payment availability.

Figure 3: Payoffs at Different Hours



Notes: This figure shows the estimates of α_t with 10 AM normalized to 0 from Equation 1. Different tiers are labeled using different colors. The x-axis is the ending hours of auctions (i.e., the hour of the day) and the y-axis is the estimated α_t. As the highest bid is not conditional on selling the objects, some less expensive cars show higher payoffs in some periods.

4.3 Sellers Learn to Choose the Ending Hours

4.3.1 Sellers gradually focus on a smaller set of ending hours

To show that the sellers are learning to improve their ending hour choices, I first document that the sellers initially start with a broad set of ending hours and then gradually focus on a couple of ending hours. I define the experience as how many auctions a seller has hosted for a particular tier. I assume that the experience is exogenous, as the sellers do not know when their clients will find them to conduct these auctions. In other words, the random arrival process of the clients creates the exogeneity of the experience variable.[23]

When calculating the average number of ending hours chosen, I aggregate experience by every 100 auctions as experience levels. Figure 4 illustrates the number of unique ending hours chosen by sellers, averaged across sellers and car tiers, at different levels of experience. The x-axis rep-

[23]This is evidenced by the large variation in the number of auctions that a seller holds per year. Although it could be true that sellers with better auction performance attract more clients, potentially threatening the exogeneity assumption, this would require clients to have a comprehensive understanding of the sellers' past performance. Given the large number of sellers on the platform, it is unlikely that clients can conduct comprehensive and exhaustive analyses of each seller's performance.

resents the experience level, and the y-axis shows the average number of unique hours chosen by sellers within that experience level. The figure shows a clear downward trend, indicating that as sellers gain more experience on the platform, they tend to choose a smaller set of ending hours for their auctions. Initially, sellers select from approximately five unique hours, but this number decreases steadily, reaching about two unique hours as their experience level approaches 20 (i.e., 2,000 auctions). This pattern potentially suggests that sellers refine their strategies over time, and the decreasing number of chosen ending hours may indicate the learning process sellers undergo.

Figure 4: Number of Unique Ending Hours Chosen

Notes: This figure shows the number of unique hours chosen by the sellers, averaged across sellers and tiers for a given experience level. The x-axis is the experience level, defined as per 100 auctions. The y-axis is the number of average number of unique hours chosen by the sellers for tier in that experience level.

One may worry that this effect is due to the aggregation. In Appendix C.1, I report the results of regressing the number of unique hours chosen on the experience level. In the preferred specification, I include the seller-tier fixed effects to compare how the number of ending hours chosen changes for a seller in a given tier as the experience increases, and the results are still robust. This reinforces the confidence that at the seller-tier level, the sellers still reduce the number of ending hours chosen.

4.3.2 Sellers shift to better times

While Figure 4 shows that the sellers are concentrating on a smaller set of ending hours, it does not show which time slots the sellers are transitioning to. To this end, I divide the ending hours into four categories: default, best, better, and worst. The default is 10 AM, which is the most common ending hour for other categories of auctions on Ali Auction, as shown in Figure D.1. To categorize ending hours into best, better, and worst hours, I take the residualized hourly fixed effects from Equation 1, $\hat{\alpha}_t$, and rank them based on their magnitudes. For each tier, best is defined as the top four ending hours with the largest $\hat{\alpha}_t$'s, the better is the middle five ending hours, and the worst is the last five. As 10 AM is already defined as the default hour, it is excluded from these three bins. Based on this, I run the following regression:

$$\text{Hour Bin Share}_{b(s,k)l(s,k)} = \beta * \text{Experience Level}_{s,k} + FE_s + FE_k + \epsilon_{b(s,k)l(s,k)}, \tag{2}$$

where the dependent variable, Hour Bin Share˙b(s,k)l(s,k), is the share of the auctions in each ending hour bin b for a given seller s and tier k when the experience level is l. Experience $\text{Level}_{s,k}$ is the seller-tier-specific experience level, defined as every 100 auction intervals. FE_s and FE_k are seller-specific and tier-specific fixed effects, and $\epsilon_{b(s,k)l(s,k)}$ is the error term. The estimation results are reported in Table 2.

Table 2: Changes in Share of Ending Hour Bins with Experience Level

	Dependent Variable: Share of the Hour Category Chosen			
	Default (10 am)	Best	Better	Worst
	(1)	(2)	(3)	(4)
Experience Level	-0.005	0.006	0.011^{***}	-0.005^{**}
	(0.023)	(0.004)	(0.003)	(0.003)
Seller FE	Yes	Yes	Yes	Yes
Tier FE	Yes	Yes	Yes	Yes
Observations	103	297	528	333
Adjusted R^2	0.384	0.509	0.356	0.310

Notes: *p<0.1; **p<0.05; ***p<0.01. The table shows the regression results from Equation 2 and each column shows how the shares of the auctions released by a seller change with the experience level. The standard errors are clustered at the seller level.

Column (1) of Table 2 shows the relationship between experience level and the share of auctions ending at the default hour (10 AM). The coefficient for experience level is negative but not statistically significant, suggesting that while there is a tendency for experienced sellers to choose the default hour less frequently, this trend is not strongly pronounced. In Column (2), which examines the share of auctions ending at the best-performing hours, the coefficient for experience level is positive but not statistically significant, indicating that while the sellers may increase the share of the best hours chosen, the result is not robust. Column (3) analyzes the better-performing hours, where the positive and highly significant coefficient suggests that as sellers gain more experience, they release more auctions at better-performing hours. Column (4) investigates the worst-performing hours, showing a significant negative relationship with experience level. This result indicates that more experienced sellers are less likely to choose the worst-performing hours, reflecting their improved ability to avoid suboptimal ending times and suggesting that the source for the increased share in the better-performing hours is mainly from the worst-performing ones.

Overall, the table highlights that with increasing experience, sellers refine their strategies by moving away from default and worst-performing hours and favoring best and middle-performing hours. This evolution in strategy provides additional evidence suggesting that sellers are learning to improve their ending hour choices as they accumulate experience on the platform.

4.3.3 Auction performance improves

I proceed to show that as the sellers move to the best and better ending hours and abandon the default and worst ending hours, the auction outcomes improve. To see this, I run the following regression

$$\text{Auction Outcome}_a = \alpha \text{Experience}_a + \text{Auction Controls}_a \beta + FE_{s(a)\times k(a)} + FE_{k(a)*y(a)} + \epsilon_{at}, \quad (3)$$

where the Auction Outcome$_a$ is the indicator for selling or not, the payoff, and the payoff conditional on sold, respectively. The Experience$_a$ is the number of auctions the seller s has released in this particular tier k that the auction a is in. Auction Controls$_a$ is the auction-related characteristics, same as in Equation 1. I include seller-tier fixed effects ($FE_{k(a)\times s(a)}$) and tier-year ($FE_{k(a)*Y(a)}$) fixed effects to control for seller-tier-specific unobservables and time-varying tier-specific unobservables. This regression compares the outcomes of the auction released within the same time window (Year-Month level) for a given seller in a particular tier but with different experiences with the market. The results are reported in Table 3.

Table 3: Auction Outcome Changes with Experience

	Dependent variable:		
	1(Sold)	Payoff	Payoff (cond)
	(1)	(2)	(3)
Experience (in 100s)	−0.001	32.238	55.736***
	(0.001)	(33.880)	(21.586)
Auction Controls	Yes	Yes	Yes
Seller x Tier FE	Yes	Yes	Yes
Tier x Year FE	Yes	Yes	Yes
Mean Dep. Var.	0.68	6400.92	9476.52
Observations	47,472	47,472	32,065
Adjusted R^2	0.829	0.431	0.523

Notes: *p<0.1; **p<0.05; ***p<0.01. The table shows the regression results from Equation 3 and each column shows how the auction outcomes change with the experience that a seller has. The independent variable, experience, is divided by 100. The standard errors are clustered at the seller level.

Column (1) of Table 3 shows the relationship between experience and the probability of an item being sold. The coefficient for experience level is negative but not statistically significant, indicating that seller experience does not significantly impact the likelihood of an item being sold. Moreover, the economic magnitude is also very small. For every 100 auctions, the selling probabilities will only change by 0.1 percentage point, compared with the mean level of the selling probability of 68%.

Columns (2) and (3) focus on the payoffs of the auctions. While the dependent variable in Column (2) is the unconditional payoff, regardless of whether the auction has been sold, Column (3) shows the payoff conditional on the item being sold. The coefficient for experience is positive but not statistically significant in Column (2), suggesting that overall, experience does not have a significant effect on the highest bid received across all auctions. In Column (3), the positive and highly significant coefficient indicates that as sellers gain more experience, the highest bids they receive, conditional on the item being sold, increase significantly. This result highlights the value of experience in securing higher payoffs when sales occur. In particular, as the experience increases by 100 auctions, the payoff will increase by $56, corresponding to 0.6% change compared with the mean payoff conditional on selling.

Overall, Table 3 shows that while experience does not significantly impact the likelihood of an item being sold or the highest bid received across all auctions, it significantly enhances the highest bids received when sales do occur, suggesting that the sellers are improving their auctions' outcome over time.

4.4 Own Data and Others' Data in Sellers' Learning

As introduced in Section 2.3, the sellers have access to their own auctions' performance, and they are able to retrieve their competitors' information. I refer to these two sources of information as their own data and others' data, respectively. One concern is that these sellers may not actively acquire the information about others and thus, do not respond to others' data. To address this, I first present evidence that sellers respond to these two data sources. Then, I show that they have differential preferences over these two data sources as they accumulate experience on the platform.

To examine how the sellers use information, I define the unexpected payoffs as the difference between the most recent auction's payoff and that of all the auctions before for a given tier k and hour t. Specifically, it is calculated as below:

$$\text{Unexpected Payoff}_{k,t|a-1} = \frac{1}{|N_{k,t|a-1}|}\sum \text{Payoff}_{k,t|a-1} - \frac{1}{\sum_{A=a-2,\cdots,1}|N_{k,t|A}|}\sum_{A=a-2,\cdots,1} \text{Payoff}_{k,t|A}, \tag{4}$$

I abuse the notation of a here and let it denote the auction occasion. Hence, $a-1$ is the last auction in tier k and hour t. $\frac{1}{|N_{k,t|a-1}|}\sum \text{Payoff}_{k,t|a-1}$ is the average payoff in the last auctions with $|N_{k,t|a-1}|$ denoting the number of auctions, and $\frac{1}{\sum_{A=a-2,\cdots,1}|N_{k,t|A}|}\sum_{A=a-2,\cdots,1} \text{Payoff}_{k,t|A}$ is the average payoffs of the auctions conducted before the occasion $a-1$. This definition of unexpected payoffs is consistent with the definition of surprises used in macroeconomics and finance literature (e.g., Scotti 2016).

Based on their own data and others' data, the seller can observe two unexpected payoffs: their own unexpected payoffs and others' unexpected payoffs. Specifically, own unexpected payoffs are formed using their own data ($\mathcal{I}_O$) while others' unexpected payoffs are formed using others' data

($\mathcal{I}_P$):

$$\begin{aligned} \text{Own Unexpected Payoffs}_{k,t|a_s-1}|\mathcal{I}_O =& \frac{1}{|N_{k,t|a_s-1}|}\sum \text{Payoff}_{k,t|a_s-1} \\ &- \frac{1}{\sum_{A_s=a_s-2,\cdots,1}|N_{k,t|A_s}|}\sum_{A_s=a_s-2,\cdots,1}\text{Payoff}_{k,t|A_s}, \end{aligned} \tag{5}$$

$$\begin{aligned} \text{Others' Unexpected Payoffs}_{k,t|a'_{s'}-1}|\mathcal{I}_P =& \frac{1}{|N_{k,t|a'_{s'}-1}|}\sum \text{Payoff}_{k,t|a'_{s'}-1} \\ &- \frac{1}{\sum_{A'_{s'}=a'_{s'}-2,\cdots,1}|N_{k,t|A'_{s'}}|}\sum_{A'_{s'}=a'_{s'}-2,\cdots,1}\text{Payoff}_{k,t|A'_{s'}}, \end{aligned} \tag{6}$$

where $a-1$ and $a'-1$ are the last auctions released by the focal seller s and other sellers, respectively, and A_s and $A'_{s'}$ are the sets of past auctions by the seller and other sellers.

4.4.1 Sellers use their own data and others' data in learning

To show that these sellers respond to both sources of information into account, I regress sellers' decisions to change the ending hours based on the unexpected payoffs that they receive. Specifically, I run the following regression:

$$\begin{aligned} 1(\text{Switched}) =& \alpha_1(\text{Own Unexpected Payoffs}_{k,t|a-1}|\mathcal{I}_O) + \alpha_2(\text{Others' Unexpected Payoff}_{k,t|a-1}|\mathcal{I}_P) \\ &+ FE_{k(a)*s(a)} + FE_{y(a)*m(a)} + FE_t, \end{aligned} \tag{7}$$

where the dependent variable is an indicator of whether the seller has switched away from the last chosen time. The (Own Unexpected Payoffs$_{k,t|a-1}|\mathcal{I}_O$) and (Others' Unexpected Payoff$_{k,t|a-1}|\mathcal{I}_P$) are the unexpected payoffs defined in Equations 5 and 6. $FE_{k(a)*s}$ will absorb tier-seller-specific unobservables and $FE_{y(a)*m(a)}$ will absorb year-month seasonality. I also include hour-specific fixed effects (FE_t) to absorb time-invariant hour-specific unobservables.

The estimation results are reported in Column (1) of Table 4. Column (1) shows that both their own unexpected payoffs and others' unexpected payoffs have a significant negative impact on the likelihood of changing the starting time. Moreover, the magnitudes of the estimates are larger for their own unexpected payoffs than others' unexpected payoffs. For \$10,000 increase in the own unexpected payoffs, the switching probabilities will decrease by 2.2 percentage points, translating into 5% of the average switching probabilities. For the same increase in others' unexpected payoffs, the magnitude is 0.7 percentage points, translating into 2% of the average switching probabilities. This indicates that unexpected outcomes, both from the seller's own auctions and from competitors' auctions, reduce the probability of altering starting times, implying that the sellers take both data sources into consideration when making decisions.

Table 4: How Firms Decide to Switch

	Dependent variable:	
	$\mathbb{I}$(Whether Changed Starting Time)	
	(1)	(2)
Own Unexpected Payoffs (in \$10,000s)	-0.022^{**}	-0.005
	(0.009)	(0.009)
Others' Unexpected Payoffs (in \$10,000s)	-0.007^{***}	-0.009^{*}
	(0.003)	(0.005)
Experience (in 100s)		-0.002
		(0.006)
Own Unexpected Payoffs*Expr.		-0.005^{*}
		(0.002)
Others' Unexpected Payoffs*Expr.		0.0003
		(0.0005)
Seller x Tier FE	Yes	Yes
Year x Month FE	Yes	Yes
HOD FE	Yes	Yes
Mean Dep. Var.	0.46	0.46
Observations	44,959	44,959
Adjusted R^2	0.234	0.238

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Column (1) shows the estimation results from Equation 7 and Column (2) shows the estimation results by interacting the own unexpected payoffs and others' unexpected payoffs with experience. The standard errors are clustered at the seller level.

4.4.2 Sellers show evolving differential preferences for data sources

I further examine how the tenure on the platform affects the sellers' preference for different data sources. Specifically, I interact Own Unexpected Payoffs$_{k,t|a-1}|\mathcal{I}_O$ and Others' Unexpected Payoffs$_{k,t|a-1}|\mathcal{I}_P$ in Equation 7 with experience that the seller has at the occasion a. The estimation results are reported in Column (2) of Table 4.

While the coefficient for own unexpected payoffs remains negative but becomes insignificant, the interaction term for own unexpected payoffs and experience is significant and negative. This suggests that as sellers gain more experience, the negative impact of their own unexpected payoffs on the likelihood of changing starting times becomes more pronounced. Others' unexpected payoffs still have a significant negative impact, and the interaction term for others' unexpected payoffs and experience is positive but insignificant. Using the point estimates, one can calculate that at roughly 75 auctions, the two unexpected payoffs will have similar effects on sellers' decisions to change their current ending hours. This result implies that the sellers initially rely heavily on others' data to make their decisions on whether to change their ending hour choices. However, as they accumulate experience on the platform, they start to rely more on their own data instead of that of others, highlighting evolving preferences for two sources of data.

Discussion Given the current data, I am unable to explore the underlying mechanisms behind why sellers have these evolving preferences for their own data as they gain experience. Detailed data on how sellers process information from these two different sources and form their beliefs would be needed to investigate this further. Several explanations could account for this finding. While I can rule out some explanations through empirical context, other stories remain plausible.

First, sellers may not trust the information they retrieve about others' auction performance (Neumann et al., 2019). As they stay longer on the platform, they may gradually recognize potential errors in others' performance data. However, in this particular context, sellers can retrieve accurate information about the performance of other auctions, as all information is transparent. Hence, this should not be the case. Moreover, different forms of presentation of their own and others' information may lead sellers to rely more on their own data (Conlon et al., 2022b). Given that the own data and others' data contain the same set of information and are presented similarly on the website, this should also not be the case. Furthermore, as sellers gain more experience on the platform, they should be better able to interpret others' data. Consequently, if this explanation were true, we should not observe sellers relying more on their own data than on others' data.

Having eliminated these two explanations using the empirical context, I now discuss three other explanations that I cannot rule out. Conlon et al. (2022b) use lab experiments and find that when individuals exert effort by trying out different options to generate their own information, they tend to rely more on their own information. This finding is consistent with the results here. As sellers try out different ending hours and accumulate more experience, they become more responsive to their own data.

Another explanation is the ownership effect documented by Hartzmark et al. (2021). As sellers generate more data from their own auctions, they develop a sense of ownership and, thus, rely more on their own data.

While the previous two explanations focus on behavioral factors, a third explanation might be that sellers are rationally inattentive to the two sources of information (for a review, see Maćkowiak et al. 2023). Since their own data and others' data are substitutes, sellers may choose to focus on their own data as they accumulate more, due to the associated lower cost. Although the cost of acquiring information itself cannot explain the finding[24], there might be other costs associated with processing the information, which could contribute to sellers' gradual reliance on their own data.

Unfortunately, the current data cannot disentangle these alternative stories. I leave this to future research and take a reduced-form stance on how the sellers are weighing different information in the structural model.

In this section, I show that focusing on the ending hours is important for the firms, as bidders are most active in the last hour of the auction, and different ending hours have different payoffs for similar auctions. I further present evidence that sellers learn to change their ending hours over time by gradually focusing on a smaller set of ending hours with higher payoffs. As a result, the auction outcomes improve. Then, I document that the sellers incorporate both their own data and others' data in their learning process. In particular, as sellers gain more experience on the platform, they rely more on their data, as evidenced by that they respond more to unexpected payoffs from their own data.

[24] As the sellers set up the system to acquire others' information, the information acquiring cost has been sunk.

5 Consumer: Bidding in Commercial Used-Car Auctions

I estimate a structural model of bidders' bidding for the commercial used cars and sellers' choices for the ending hours while learning about the expected payoffs for these ending hours. The goal of the structural model is to evaluate the consequence of the sellers' learning and their preferences towards their own data.

On the bidder side, the bidders decide on the participation of the auctions and decide on how much to bid. As used cars are highly idiosyncratic, I explicitly control for unobserved heterogeneity of the cars when recovering the bidders' valuation. On the seller side, given the bidders' valuation, expected arrival process of the bidders, and expected competition for different hours, they make entry decisions. While the sellers have a homogeneous learning process, the sellers have heterogeneous beliefs given their own data, others' data, and their experience level, which drive the sellers to make different entry decisions.

As shown in Figure 1, the structural model has three stages. First, sellers enter the auction. Then, given the auctions, the bidders enter. After the bidders' entry, the qualified bidders participate in an auction following the ascending English auction format. I present and estimate the model in reverse order, starting from the bidding stage.

5.1 Qualified Bidders Bidding in the Auctions

To recover the bidders' valuation distribution, I adapt Freyberger and Larsen (2022) and borrow their notations.[25] Conditional on seller and bidder entry, the platform has a set of ascending English auctions, $\mathcal{A}_{dkt}$, available auctions for a particular calendar day d, category k, and hour of the day t. A set of N_a bidders participate in the auction a, where $a \in \mathcal{A}_{dkt}$. Let $i \in N_a$ be the bidders and s be the seller of auction a. For the exposition simplicity, I will omit the subscript d.

Following Freyberger and Larsen (2022), I make the following assumptions:

Assumption 1. For a given auction a, assume that the valuation of the bidder i in this auction takes

[25] Different from the context that Freyberger and Larsen (2022) consider, I directly observe the number of potential bidders (N in their notation). One object of their framework is to identify the N, and I relax the assumptions associated with N. Since Ali Auction has an open reserve price setting, I focus on the open reserve price case discussed in their paper.

the form of

$$V_{ai} = X_a + U_{ai}. \tag{8}$$

The reserve price is set according to the rule of

$$R_{as} = X_a + W_{as}, \tag{9}$$

where X_a is the unobserved heterogeneity (to econometricians) of the auctions but observable to the seller and the bidders, U_{ai} is the private valuation of the bidder, and W_{as} is the private valuation of the seller.

Assumption 1 abstracts away from the observed characteristics of the auctions.[26] It establishes that for both the valuations of the bidders and the reserve prices of the sellers, there is a common unobserved component (X_a) that is shared by both sides of the auctions.[27] While X_a is unobservable to the econometricians, the sellers and bidders observe this in auction a.

Moreover, as noted in Freyberger and Larsen (2022) and Decarolis (2018), Assumption 1 does not specify the reserve price to be optimal. Rather, it only takes this reduced-form way of setting the reserve price.

Assumption 2. Further assume $U_{ai} \perp X_a$, $W_{as} \perp X_a$, $U_{ai} \perp W_{as}$, $U_{ai} \perp U_{aj}, \forall i \neq j$ and $i, j \in N_a$, and $U_{ai}, X_a, W_{as} \perp N_a$. Let $X_a \sim F_{X_{k(a),t(a)}}$ with density $f_{X_{k(a),t(a)}}$, $U_{ai} \sim F_{U_{k(a),t(a)}}$ with density $f_{U_{k(a),t(a)}}$, $W_{as} \sim F_{W_{k(a),t(a)}}$ with density $f_{W_{k(a),t(a)}}$.

Assumption 2 assumes that the independence between the bidder i's idiosyncratic valuation with the unobserved auction characteristics $(U_{ai} \perp X_a)$, independence between the seller s's idiosyncratic valuation with the unobserved auction characteristics $(W_{as} \perp X_a)$, and independence between two bidders in the same auction $(U_{ai} \perp U_{aj}, \forall i \neq j$ and $i, j \in N_a)$. Moreover, these valuations do not depend on N_a. In other words, this assumes that the bidders will only form their valuations of the objects after entering the auction by examining the cars closely. For the sellers, when they set the reserve prices, they do not know how many bidders will show up. Then, X_a follows the distribution of tier-hour-specific distribution that the auction a is in $(X_a \sim F_{X_{k(a),t(a)}})$.

[26] I will discuss how I account for observed characteristics in Section 5.3.2.

[27] Although the reserve price is set by the clients of these sellers, I refer to them as the sellers for exposition simplicity.

Similarly, U_{ai} and W_{as} follow their tier-hour-specific distributions ($F_{U_{k(a),t(a)}}$ and $F_{W_{k(a),t(a)}}$), respectively.

Recall that Ali Auction uses ascending English auctions. Let the minimum incremental bids for each auction a be η_a. Then, conditional on the number of qualified bidders (i.e., those who have paid the participation deposits), the best response for the bidders with a valuation v:

Lemma 3. The second and third-highest valued bidders bid their valuations. $b^*_{\{2:N_a\}} = v_{\{2:N_a\}}$ and $b^*_{\{3:N_a\}} = v_{\{3:N_a\}}$. The highest-valued bidder will bid $b^*_{\{1:N_a\}} = b^*_{\{2:N_a\}} + \eta_a = v_{\{2:N_a\}} + \eta_a$

Proof. For the second and third-highest valued bidders, bidding more than the valuations will have negative payoffs while bidding less will lead to regret with a lowered probability of winning. The highest-valued bidder can win the auction with a positive payoff by bidding marginally higher than the second-highest bidder's valuation. □

5.2 Bidder Entry

Bidder entry will take a reduced-form approximation with Poisson arrival rates for each ending hour and tier following Hortaçsu and Bajari (2003) with a mean arrival rate of λ_{ba} for auction a in category k at time t with subscript b to denote the bidders. For the tier k and hour t that the auction a is in:

$$\log(\lambda_{ba}) = \alpha_t + \alpha_1 * \text{Effective Reserve Price}_a + \alpha_2 \sum \mathbb{I}\{-a \in \{\mathcal{A}_{kt}\}\} + \alpha_3 * \text{Year}_a + \alpha_4 * \text{No. of Images}_a \tag{10}$$

Different from Hortaçsu and Bajari (2003), I also capture the competition effect among the auctions through the competition effect in the term $\sum \mathbb{I}\{-a \in \{\mathcal{A}_{kt}\}\}$, where $\mathbb{I}(\cdot)$ is an indicator function to indicate whether other contemporaneous auctions $-a$ are in the set of $\mathcal{A}_{kt}$, the set of auctions in category k at time t. α_1 captures the effect of the effective reserve price, as defined in Section 4.1 on bidders' entry in a reduced-form way. Year_a is the year when the auction a is hosted to capture a linear yearly trend in the number of bidders. No. of Images_a captures the number of pictures that the sellers upload, as it may provide a summary of the cars and affect the bidders' entry decisions. This formulation is motivated by what the bidders will see when they click into an auction page on Ali Auction and make entry decisions. An example of this is provided in Figure D.3.

5.3 Identification and Estimation

5.3.1 Identification

I focus on the identification of the bidders' valuation distribution for different tiers and hours, $F_{U_{k(a),t(a)}}$. The identification of the model follows from Theorem 2 in Freyberger and Larsen (2022). Different from the case that Freyberger and Larsen (2022) consider, I directly observe the number of potential bidders (i.e., qualified bidders who have paid the participation deposit), and hence, do not need to recover N_a. I normalize the mean of $X_{k(a),t}$ to be zero as the distributions of $X_{k(a),t}$ and $W_{k(a),t}$ can only be identified up to a location shift.

Given the above assumptions, the joint distribution of the second- and third-highest bids are first identified for auctions with second- and third-highest bids exceeding the reserve price. Moreover, following from Unjy (2004), the joint distribution of the second- and third-highest bidders only depends on the marginal distribution of the bidders' valuation, the distribution of $F_{U_{k(a),t(a)}}$ is identified.

5.3.2 Estimation

Following Freyberger and Larsen (2022) by taking logs of the reserve prices and Haile et al. (2003) to homogenize the log of reserve prices, I run the following regression at the auction tier level k to homogenize the reserve price:

$$\log(R)_a = Z_a'\delta + \log(X)_a + \log(W)_a + \epsilon_a, \tag{11}$$

where Z is the observed auction characteristics. The homogenized reserve price $\widetilde{\log(R)}_a$ is $\widetilde{\log(R)}_a = \log(R)_a - Z_a'\hat{\delta}$. Each bid is also homogenized by the same $Z'\hat{\delta}$ as $\widetilde{\log(b)}_{ai} = \log(b)_{ai} - Z_a'\hat{\beta}$.

I impose a parametric assumption on the distribution of the $U_{k,t}$, $W_{k,t}$, and $X_{k,t}$ that they follow log-normal distributions. Hence, $\log(U_{k,t}) \sim N(\mu_{U_{k,t}}, \sigma_{U_{k,t}})$, $\log(W)_{k,t} \sim N(\mu_{W_{k,t}}, \sigma_{W_{k,t}})$, and

$\log(X_{k,t}) \sim N(0, \sigma_{X_{k,t}})$.[28]

Given the reserve price of an auction $\log(R)_a$, three cases are possible. First, no second or third-highest bids are submitted. This corresponds to the scenarios where only one bid is submitted or no bids are submitted. Let an indicator I_{1_a} to denote if this is true for auction a. Second, only the second-highest bid is observed, and denote this case as I_{2_a}. Third, both the second and third-highest bids are submitted, and the indicator for this case is I_{a_3}.

For each case, I derive the probability of observing such case as $\mathbb{P}_{1_a}$, $\mathbb{P}_{2_a}$, and $\mathbb{P}_{3_a}$ and for the log-likelihood for all the auctions that I consider for a particular tier k at hour t:

$$ll_{k,t} = \sum_{a \in k,t} I_{1_a} \log(\mathbb{P}_{1_a}) + I_{2_a} \log(\mathbb{P}_{2_a}) + I_{3_a} \log(\mathbb{P}_{3_a}) \tag{12}$$

I estimate the distributions of $U_{k,t}$, $W_{k,t}$, and $X_{k,t}$ for each tier k and hour t combination. The details for the estimate are in Appendix B.

6 Seller: Hour-of-the-Day Entry with Adaptive Learning from Two Data Sources

On the seller side, the sellers make decisions on when to end their auctions based on the expected payoffs for different time periods. Let the profit function of a seller s for auction a that are ended at hour t be:

$$\pi_{at} = \gamma_t + \beta \mathbb{E}(V_{at}) + \varepsilon_{at} \tag{13}$$

where γ_t is the hour-specific fixed effects to capture potential time-specific costs or preferences (e.g. 10 AM, the default time). $\mathbb{E}(V_{at})$ is the auction-hour-specific payoffs. ε_{at} is auction-hour specific unobservables.

As shown in the reduced-form evidence, both own data and others' data affect the sellers' choices of the ending hours. To capture this, I allow the sellers to form two expectations about the expected payoffs from their own data and others' data, respectively. I denote these two expected payoffs as $\mathbb{E}(V_{at}|\mathcal{I}_O)$ and $\mathbb{E}(V_{at}|\mathcal{I}_P)$, where $\mathcal{I}_O$ indicates their own data and $\mathcal{I}_P$ denotes others' data.

[28]This parametric distribution fulfills the Assumptions 2 and 3 in Freyberger and Larsen (2022).

Moreover, the reduced-form evidence shows that as the sellers' tenure on the platform increases, they care more about their own data than others' data. To capture this, I allow the expected payoffs to take a weighted average between the expected payoffs formed using the seller's own data and others' data. The weight is allowed to be varying between 0 and 1 as the seller's experience changes. Specifically, I re-write $\mathbb{E}(V_{at})$ in Equation 13 as:

$$\mathbb{E}(V_{at}) = \frac{\rho \cdot expr}{1 + \rho \cdot expr}\mathbb{E}(V_{at}|\mathcal{I}_O) + \frac{1}{1 + \rho \cdot expr}\mathbb{E}(V_{at}|\mathcal{I}_P). \tag{14}$$

Now, I discuss how the sellers form the expected payoffs from the two data sources.

6.1 Formation of $\mathbb{E}(V_{at}|\mathcal{I}_O)$ and $\mathbb{E}(V_{at}|\mathcal{I}_P)$

To form the expected payoff for an auction ending at different hours, the number of residual bidders and bidders' valuation matter. In particular, I assume that the sellers know the underlying bidders' valuation distribution, but only form the expectations about the number of bidders based on their own data $\mathcal{I}_O$ and others data $\mathcal{I}_P$.[29]

To show how the $\mathbb{E}(V_{at})|\cdot$ depends on the number of bidders and the bidders' valuation, I drop the source of the dataset for now to facilitate exposition. Let $n_{a_t} \sim Poisson(\lambda_{N_{a,t}})$ be the number of bidders in an auction following a Poisson distribution. Denote bidders' valuation distribution for the particular tier $k(a)$ and hour t, $f_{v_{k(a),t}}$. Then, for $\mathbb{E}(V_{at})|\cdot$:

$$\mathbb{E}(V_{at}|\cdot) = \int v_{k(a),t} \cdot f_{v_{2:n_{a_t}}} dv, \tag{15}$$

where $f_{v_{2:n_{a_t}}}$ is the probability density function of second-order statistics given the underlying valuation distribution is $f_{v_{k(a),t}}$ and takes the form of:

$$f_{v_{2:n_{a_t}}} = (n_{a_t} - 1)n_{a_t} f_{v_{k(a),t}}(v)[F_{v_{k(a),t}}(v)]^{n_{a_t}-2}(1 - F_{v_{k(a),t}}(v)) \tag{16}$$

[29]The assumption that the sellers know the underlying bidders' valuation can be relaxed. In principle, the sellers can also form expectations about the underlying demand distribution. This assumption is used here to ease the computational burden.

6.2 Adaptive Learning to Form $\lambda_{N_{k(a),t}}$

As mentioned above, the sellers only form the expectation about the number of bidders based on their own data and others' data. To form the expectation for the mean arrival rates, $\lambda_{N_{k(a),t}}|\cdot$, for the auction a in tier k at period t, I assume that the sellers use adaptive learning to form the expectation given the data that they have. The sellers know the functional form as in Equation 10, but will re-estimate the parameters each time when they make the decisions using two data sources:

$$\begin{aligned}\log(\lambda_{N_{k(a),t}}|\mathcal{I}_O) &= \alpha_{t,O} + \alpha_{1,O} * \text{ERP}_a + \alpha_{2,O} \sum \mathbb{I}\{-a \in \{\mathcal{A}_{kt}\}\} + \alpha_{3,O} * \text{Year} + \alpha_{4,O} * \text{No. Images} \\ \log(\lambda_{N_{k(a),t}}|\mathcal{I}_P) &= \alpha_{t,P} + \alpha_{1,P} * \text{ERP}_a + \alpha_{2,P} \sum \mathbb{I}\{-a \in \{\mathcal{A}_{kt}\}\} + \alpha_{3,P} * \text{Year} + \alpha_{4,P} * \text{No. Images}\end{aligned} \tag{17}$$

After estimating the $\boldsymbol{\alpha}|\mathcal{I}_O$ and $\boldsymbol{\alpha}|\mathcal{I}_P$, to form the expectations about the mean arrival rates for the number of bidders, the sellers also need to form the belief about the number of expected competitors $\mathbb{E}(\sum \mathbb{I}\{-a \in \{\mathcal{A}_{kt}\}\})$. I assume that the number of competing auctions also follows a Poisson process with a linear yearly trend:

$$\log(\lambda_{-a'}) = \kappa \text{Year} \tag{18}$$

Using their own and others' information, the sellers also adaptively learn about the arrival process of the competing auctions defined as all auctions other than the focal auction on the same day across all hours:

$$\begin{aligned}\log(\lambda_{-a'}|\mathcal{I}_O) &= \kappa_O \text{Year}'_a \\ \log(\lambda_{-a'}|\mathcal{I}_P) &= \kappa_P \text{Year}'_a\end{aligned} \tag{19}$$

where I abuse the notation to let $-a'$ be the number of competing auctions that a focal auction a' has in $\mathcal{I}_O$ and $\mathcal{I}_P$, respectively.

Then, for a given auction's year, the sellers can form the expected number of bidders for a given day, as $\lambda_{-a'}|I_O = \hat{\kappa_O} Year_a$ and $\lambda_{-a'}|I_P = \hat{\kappa_P} Year_a$.

6.3 Equilibrium

I define the following as the (self-aware) equilibrium strategy of the sellers (Čopič and Galeotti, 2005; Cramerer et al., 2004). Specifically, sellers with the information at choice occasion a, $\mathcal{I}_a = \mathcal{I}_{a,O} \cup \mathcal{I}_{a,P}$ believe all other sellers have the information $\mathcal{I}_a$, and they behave the same. Each seller chooses the action that maximizes their expected payoffs. In this equilibrium, sellers exhibit mutual rationality in their choices of actions given their beliefs. Different from the Nash equilibrium concept, I relax the assumption on mutual consistency in the sense that sellers are mutually consistent within their own type (defined by their information set) but are not mutually consistent across different types.

As a result, to form the expected number of bidders, the sellers first form the expectation of the number of competitors for each hour t:

$$\begin{aligned} \lambda_{-a',t}|\mathcal{I}_O &= \lambda_{-a'}|\mathcal{I}_O * \mathbb{P}_{at}, \\ \lambda_{-a',t}|\mathcal{I}_P &= \lambda_{-a'}|\mathcal{I}_P * \mathbb{P}_{at}, \end{aligned} \tag{20}$$

where $\mathbb{P}_{at}$ is the equilibrium for the seller to choose the hour t for auction a.

Given the number of competing auctions, $n_{-at,O} \sim Poisson(\hat{\lambda}_{-a',t}|\mathcal{I}_O)$ and $n_{-at,P} \sim Poisson(\hat{\lambda}_{-a',t}|\mathcal{I}_P)$, the sellers can form the expected bidders' arrival rates $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_O$ and $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_P$ following Equation 17 with auction characteristics and the estimates of $\hat{\boldsymbol{\alpha}}|\mathcal{I}_O$ and $\hat{\boldsymbol{\alpha}}|\mathcal{I}_P$. For the number of bidders, $n_{at,O} \sim Poisson(\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_O)$ and $n_{at,P} \sim Poisson(\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_P)$, the sellers can form $\mathbb{E}(V_{at}|\mathcal{I}_O)$ and $\mathbb{E}(V_{at}|\mathcal{I}_P)$ and form the weighted average of $\mathbb{E}(V_{at})$ from Equation 14.

Assume that ε_{at} is Type 1 Extreme Value (T1EV) distributed. Then, we have the equilibrium choice of probability in logit form:

$$\mathbb{P}_{at} = \frac{\pi_{at}}{\sum_{T=9\cdots24} \pi_{aT}}, \tag{21}$$

where

$$\pi_{at} = \gamma_t + \beta\left(\frac{\rho \cdot expr}{1+\rho \cdot expr}\mathbb{E}(V_{at}|\mathcal{I}_O) + \frac{1}{1+\rho \cdot expr}\mathbb{E}(V_{at}|\mathcal{I}_P)\right) \tag{22}$$

6.4 Identification and Estimation

6.4.1 Identification

When the sellers first list their auctions, they do not have any own data. In this case, the sellers will only rely on the prediction based on others' data. The choices of the hours based on the payoffs give the identification for β. The time-fixed effects, γ_t, are identified based on the sellers' persistence choices for a specific hour. Given β and γ_t, the changes in the sellers' choices based on the differences in the payoffs between the expected payoffs based on their own data and others' data inform the ρ.

6.4.2 Estimation

I estimate the seller's parameters, γ_t, β, and ρ using maximum likelihood. For each auction a that the seller s has, I first estimate the Poisson arrival process of the competitors as in Equation 19 based on the sellers' own data and others' data to form the expectations of $\hat{\lambda}_{-a'}|\mathcal{I}_O$ and $\hat{\lambda}_{-a'}|\mathcal{I}_P$. Following the Ellickson and Sanjog (2011), I first calculate the conditional choice probabilities (CCP) for the seller based on the data they have, and form $\hat{\lambda}_{-a',t}|\mathcal{I}_O$ and $\hat{\lambda}_{-a',t}|\mathcal{I}_P$. Given the arrival rates of the competitors for each hour, I then construct the prediction for the bidder's arrival rates $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_O$ and $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_P$.

I take the consumer valuation distribution estimated in Section 5 and $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_O$ and $\hat{\lambda}_{N_{k(a),t}}|\mathcal{I}_P$ to form the predictions for the expected payoffs based on own data and others data. Then, they form the log-likelihood based on the model-predicted choices from the sellers. The details of the estimation are reported in Appendix B

7 Results

7.1 Bidders' Valuation Distribution

Figure 5 presents the expected valuations by hour of the day across five different tiers of auctions, with each panel corresponding to a specific tier. Overall, these figures show significant fluctuations in bidders' valuations throughout the day with notable peaks and drops.

Panel (a) illustrates the expected valuations for Tier 1, with notable peaks around 4 PM. While the valuation starts high at 9 AM, it gradually decreases and reaches a bottom at noon. After noon, the valuations start to increase and peak at 4 PM. In the evening and night, the valuation fluctuates with ups and downs across different time periods. It reaches the lowest point at 7 PM but bounces back to a higher level around 9 PM.

Panel (b) represents Tier 2 and shows a distinct peak at 9 PM, with valuations spiking sharply at this time. Another smaller peak is observed around 3 - 4 PM but drops sharply after that.

Tiers 3, 4, and 5, share the same peak in valuation, occurring at 6 PM. However, they show different intra-day patterns in reaching the peak and after the peak. Panel (c) shows the expected valuations for Tier 3. The graph indicates a gradual increase throughout the day, with peaks occurring at 6 PM. While the valuation drops to the lowest point at 7 PM, as time goes into the night, the valuation starts to increase.

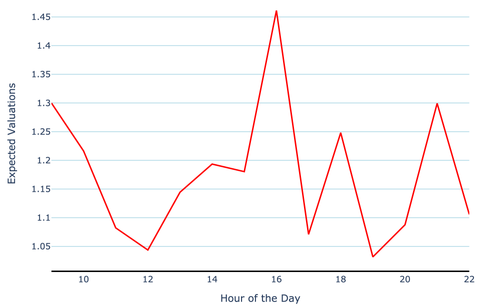
Panel (d) displays the expected valuations for Tier 4. Other than 6 PM, the valuation shows another peak early in the morning at 9 AM. There is a significant dip in valuations in the early afternoon, followed by a steady rise towards the evening. However, the valuation remains low after the time goes into the night.

Finally, Tier 5 (Panel e) shows a higher payoff in the morning and early afternoon on average, with a smaller peak at 1 PM. While the valuation starts to increase after the lowest point at 4 PM, it constantly drops towards late afternoon and evening time periods.

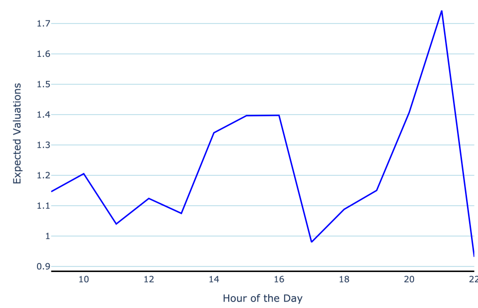
Overall, these patterns highlight the importance of strategically selecting auction ending hours based on the tier. The variability in expected valuations across different hours suggests that sellers can optimize their auction outcomes by aligning ending times with peak buyer activity periods, tailored to the specific tier they are targeting. The detailed estimation results are reported in Appendix C Table C.2.

As the estimates for the bidders' valuation will be used as inputs on the seller-side model when constructing the expected payoffs, a good fit of the model is required. To examine the fit of the estimates, I focus on the second-highest bids in the data. As shown in Section 5, the second-highest bids correspond to the bidders' second-highest valuation. I use the model predicted monetary valuation to compare that against the bids in the data. To this end, I first recover the monetary valuations implied by the estimates. I follow Freyberger and Larsen (2022) and construct the monetary

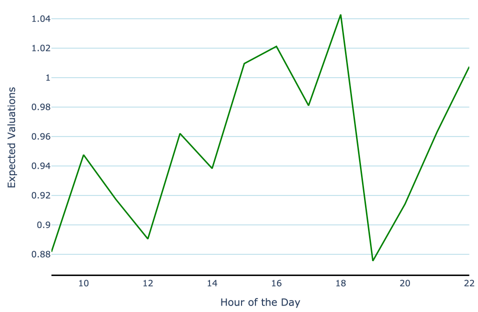
Figure 5: Bidder Valuation Distribution Across Time



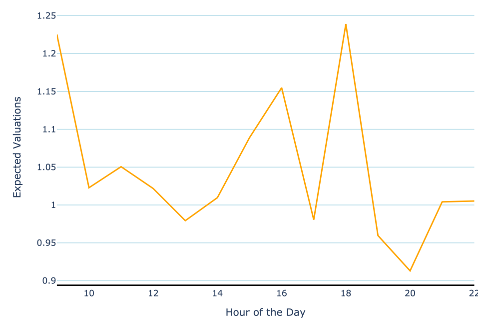
(a) Tier 1



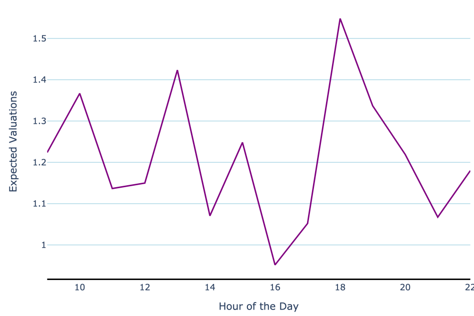
(b) Tier 2



(c) Tier 3



(d) Tier 4



(e) Tier 5

valuations for the second-highest bidder as:

$$\mathbb{E}(DV_{2:N_a}) = \mathbb{E}(Z'\beta) * \mathbb{E}(X) * \mathbb{E}(U_{2:N_a})$$

Figure 6 presents the fit of the model with five tiers in different panels. Across all tiers, the model is able to capture the trend in changes in the bids throughout the day, illustrating the good fit of the model overall. For Tiers 2, 3, and 5, the fit of the model shows a discrepancy in levels of the fit. This may be caused by the minimal incremental bids in the auctions, which limits the bidders to bid all the way up to their valuations. Otherwise, they will suffer a potential loss. However, on the seller side, for a given auction, the minimal incremental bid is the same across all hours, the level shift should not cause a concern.

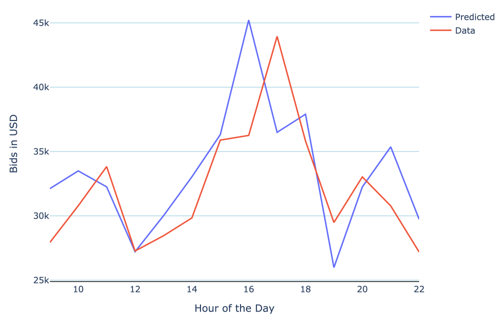
7.2 Sellers' Choices of the Ending Hours

Table 5 reports the estimates from the seller side model. All parameters are precisely estimated, and the 9 AM has been normalized as the outside option.

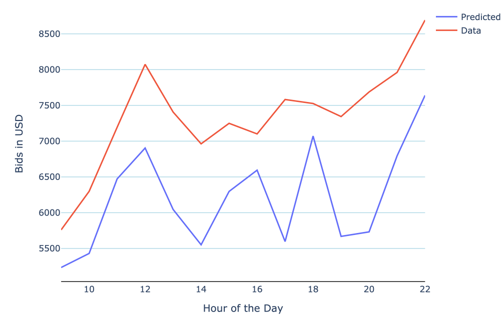
ρ governs how the sellers weigh their own data and others' data. The estimate is 0.0339, and the implied weights on two data sources are displayed in Figure 7. The solid blue line represents the weights of own data, and a dashed red line indicates the weights of others' data. Initially, when sellers have little to no experience, others' data carries significant weight, approaching nearly 1, while the weight of own data is close to 0. At around 30 auctions, the sellers weigh their own data and others' data equally. However, as sellers gain more experience, the importance of their own data increases rapidly. By the time sellers reach approximately 200 units of experience, the weight of their own data surpasses 0.85, gradually approaching 1 as experience continues to accumulate. Conversely, the weight of others' data declines sharply with increasing experience, falling below 0.2 and continuing to decrease towards zero. At the mean level of the experience that the sellers have for each tier (272 auctions), the weight of their own data is 90% versus 10% on the others' data. This pattern highlights a significant learning curve where sellers initially rely heavily on others' data but gradually shift to prioritizing their own data as they accumulate more experience.

β reflects how responsive the sellers are to the increase in the expected payoffs. To see the effects of an increase in the expected payoffs for their own data and others' data, I calculate the changes in

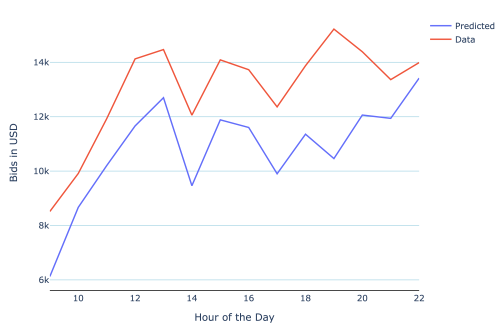
Figure 6: Fit of the Bidders' Valuation



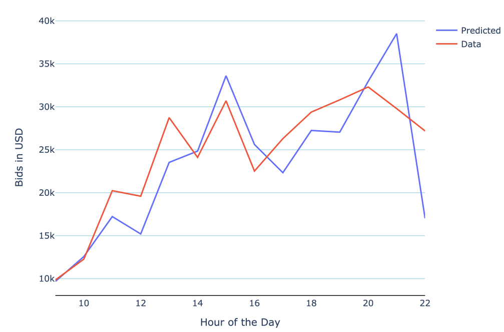
(a) Tier 1



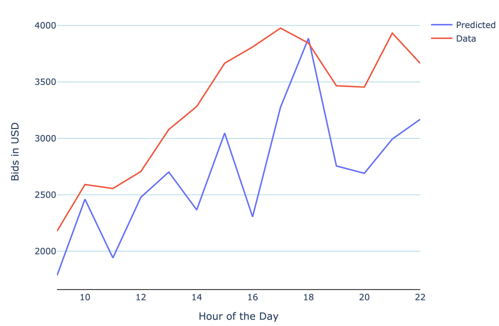
(b) Tier 2



(c) Tier 3



(d) Tier 4

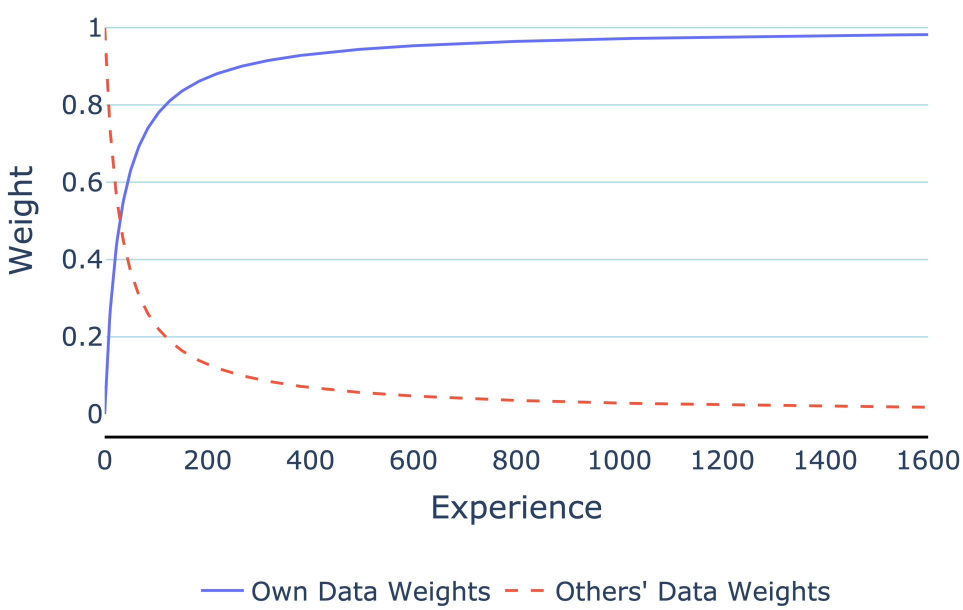


(e) Tier 5

Table 5: Parameter Estimates and Standard Errors

Parameter	Estimate	SE
ρ	0.0339	0.002
β	3.39	0.04
γ_{10}	3.4	0.08
γ_{11}	3.3	0.08
γ_{12}	1.42	0.09
γ_{13}	1.46	0.09
γ_{14}	2.06	0.08
γ_{15}	1.59	0.09
γ_{16}	1.39	0.09
γ_{17}	1.24	0.09
γ_{18}	0.68	0.09
γ_{19}	2.49	0.08
γ_{20}	3.08	0.08
γ_{21}	1.24	0.09
γ_{22}	-0.52	0.13

Figure 7: Implied Weights as Experience Changes



the choice probabilities based on a 10% increase in the expected payoffs from the two data sources, shown in Table 6.

The table highlights two features. First, the expected payoffs play an important role in the sellers' decision-making process. As the expected payoffs increase, sellers are more likely to choose the corresponding hours. Second, sellers are more responsive to changes in the expected payoffs generated by their own data. This is explained by that as the sellers gain experience on the platform, they weigh their data more than that of others. For instance, at 9 AM, the own data elasticity is 4.18, while the others' data elasticity is 2.99, indicating that sellers' decisions are more sensitive to their own data at this hour. Additionally, the highest own data elasticity occurs at 14 PM with a value of 12.77, significantly surpassing the corresponding others' data elasticity of 2.82. Overall, the table highlights the dynamic interplay between own and others' data in influencing choice probabilities, with own data generally having a stronger impact across most hours.

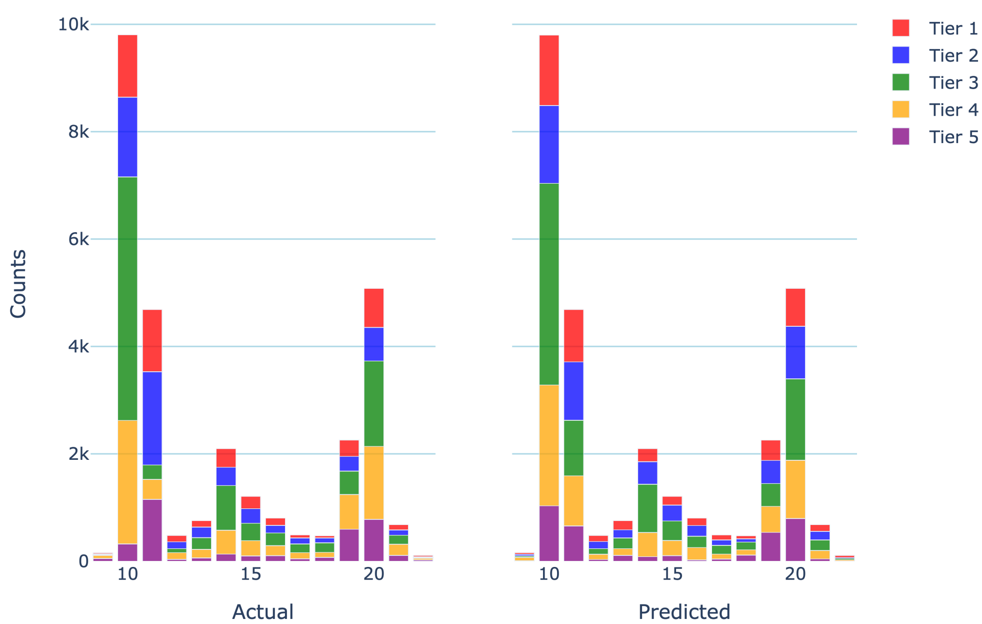
The coefficients γ reflect sellers' preferences or underlying costs for different time periods. The estimates suggest that sellers have a significant preference for certain hours over others, which aligns with a typical workday pattern in China. Notably, the coefficients for the hours from 10 AM to 11 AM are larger than the rest, indicating a strong preference for late morning slots, a time period when employees have settled into work. This is followed by a drop during the lunch break around 12 PM and 1 PM. Right after the lunch break, the estimates increase again at 2 PM. In the late afternoon, the estimates continue to decrease but rise again after dinner time in the early evening hours. Late evening is less preferred, as indicated by the smaller estimates for 9 PM and 10 PM.

To examine the fit of the model, Figure 8 presents the comparison between the data and the model's predictions. The model successfully captures the overall choices for each hour, as evidenced by the roughly equal heights of the bars. However, there are differences in the composition of each hour. For example, at 11 AM, the model predicts fewer Tier 2 auctions and more Tier 3 auctions, whereas in the data, Tier 2 has more auctions and Tier 3 only a fraction. Despite these small differences, the model generally fits the data well.

Table 6: Own Elasticities in Choice Probabilities

Hour	Own Data	Others' Data
9	4.18	2.99
10	8.278	2.18
11	6.38	1.88
12	4.25	2.15
13	5.31	3.30
14	12.77	2.82
15	11.06	3.19
16	6.76	2.70
17	6.19	2.56
18	8.45	2.96
19	7.43	2.23
20	10.30	2.01
21	8.93	2.81
22	3.80	3.85

Figure 8: Seller-side Model Fit



8 Counterfactuals

When sellers are learning to choose the ending hours on Ali Auction, both the lack of information and data preferences can lead to suboptimal decisions. To inform the platform about designing effective information-sharing policies, understanding which factor is the primary driver behind sellers' suboptimal decisions is crucial. If data preferences are the main driver, data sharing alone may not guide sellers to the best timing. The platform should also consider ways to mitigate these data preferences in addition to providing shared data.

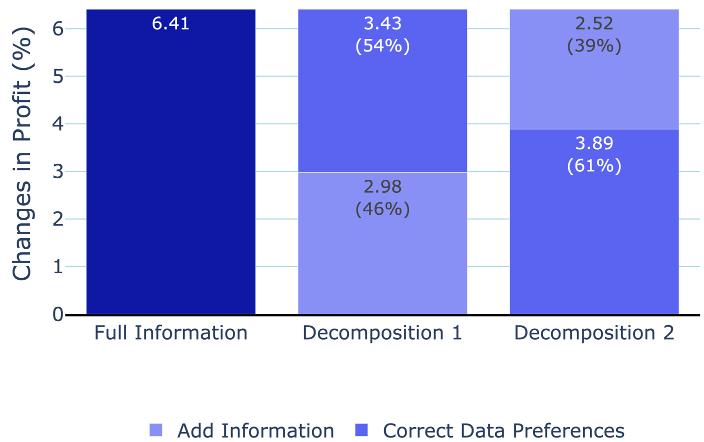
To quantify the effects of the lack of information and sellers' data preferences, I conduct three counterfactual experiments. First, I consider a scenario where all information is available and assume that sellers do not engage in any learning. This scenario corresponds to the full information structure typically considered in the literature (e.g., Seim 2006). This case will serve as an upper bound, where sellers do not suffer any potential losses related to learning or biased data preferences. I refer to this as the full information scenario.

Next, I conduct two decomposition exercises to determine whether the lack of information or data preferences is the main driver preventing sellers from achieving their potential revenue in the full information scenario. Specifically, I correct these two factors in the sellers' decision-making process and examine how much of the revenue gap between the status quo and the full information scenario can be explained by each factor. Since the sequence of correcting these two factors may affect the results, I perform two decomposition exercises with different orders of correction. In the first exercise, I start by providing the information to the sellers (i.e., sellers no longer need to learn) and then correct their data preferences. In the second exercise, I correct the sellers' data preferences first and then provide them with information.

The results of these three cases are reported in Figure 9. For comparison, I use the current revenue under the status quo as the benchmark. The first bar shows the comparison between the status quo and the full information scenario. Compared to the status quo, without any distortions from the lack of information and sellers' data preferences, sellers would see a 6.4% increase in revenue. This highlights the significant revenue losses associated with sellers' learning and their data preferences.

To determine which factor is the main driver for the revenue gap in the full information case, the

Figure 9: Sellers' Revenue Loss and Decomposition of the Main Driver



second and third bars show the results from the decomposition exercises. Specifically, the second bar shows the results from first providing the information to the sellers and then correcting their data preferences. The third bar shows the results from first correcting sellers' data preferences and then providing them with information.

Overall, both decompositions highlight that data preferences explain the majority of the revenue gap in the full information case, accounting for more than half of the potential losses in revenue for the sellers (Decomposition 1: 54% and Decomposition 2: 61%). Conversely, merely providing the information to the sellers would allow them to recover less than half of the revenue gap.

Discussion. As Ali Auction relies on auctions being successfully sold to generate revenues, the results have two implications for the platform. First, as the counterfactual results suggest, data preferences may be a barrier for the sellers to fully use the shared data. Therefore, data sharing alone cannot fully help lead the sellers to the best times on the platform.

Second, the platform can leverage sellers' preferences for their own data and consider guiding sellers to better time slots during their early stages on the platform. This will have long-lasting effects, as sellers will later heavily rely on their own auctions' performance to decide on ending hours. Leading firms to better hours will let sellers constantly reinforce their positive experiences at these hours.

Combining these two implications, the platform should consider a coordination role in guiding sellers' ending hour choices. Two possible ways to do this are by charging sellers different commission fees based on their chosen ending hours or by exploring personalized ranking on the bidder side.

Currently, Ali Auction charges a percentage of the final transaction prices for auctions that are sold. Ali Auction can consider charging different percentages for different hours chosen by the sellers. For example, it can offer discounts for more favorable hours to incentivize the sellers to choose these hours.

Alternatively, Ali Auction can present the auctions to the bidders based on their valuations. As introduced in Section 4.2.1, Ali Auction currently ranks the auctions based on their ending hours. However, the platform is capable of ranking auctions based on bidders' valuations, making the ending hour choices a less prominent decision for the sellers.

9 Conclusion

This paper investigates whether firms have preferences for their own data versus others' data when learning to improve their decisions in a new environment. Using data from the largest online auction platform in China, I analyze how the sellers use different sources of data to learn to optimize their choices of auction ending hours. To this end, I combine empirical auction literature with a structural model of sellers' adaptive learning about underlying demand and competition based on their own data and others' data.

The findings show an evolving preference among the sellers for their own data. I show that this biased preference explains the majority of the revenue gap that the sellers suffer in the status quo when compared with the full information case.

Overall, this paper underscores the importance of understanding firms' preferences for different data sources in data sharing. Since firms' preferences for their own data can be a barrier for them to fully utilize the shared data, the designers of data-sharing policies should also consider firms' data preferences for different data sources. With the presence of firms' biased preferences, a proactive role in coordinating and guiding firms to the best decisions can be considered.

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A Sample Construction

A.1 Sample Construction

In total, my data contains 409,766 auctions that ended from 6,477 sellers across all asset classes in the used-car auctions. The distribution of the auctions in each asset class is shown in Table A.1. Among all the auctions, judicial auctions, hosted by local courts, represent the largest share of all asset classes. However, Ali Auction does not charge the local courts for using the platform. For the rest of the asset classes of which Ali Auction charges service fees, commercial auction is the largest category with 27% among all auctions and 62% among the auctions other than judicial auctions.

Table A.1: Distribution of the Asset Classes in Used-Car Auctions

Ownership Category	Number of Auctions	Share in the Whole Sample
State-Owned	18,259	4.62%
Bankruptcy	15,025	4.09%
Commercial	93,125	26.79%
Investigation-Involved	3,008	0.77%
Judicial	222,932	57.02%
Financial	2,652	0.69%
Government	24,673	6.03%

Notes: This table shows the distribution of the auctions over ownership categories defined by Ali Auction in the used-car auctions. The numbers include auctions with statues of "successfully sold" and "unsold'.' While the litigation-involved auctions are the majority of the auctions, the regular auctions are the largest category that generates the revenue for Ali Auction.

I limit the sample to the period after 2020 as the commercial auctions were not active in the previous periods. This period accounts for 84.56% of all commercial auctions, as shown in Table A.2. During the period prior to 2020, 2017 was the only year that had a substantial increase in the number of auctions. This is because, during that year, other used-car platforms (not auction-based) started to develop in China. Ali Auction was actively promoting used-car auctions. Focusing on the post-2020 period is consistent with the general development of online used-car auction market trends in China that showed substantial growth after 2020.

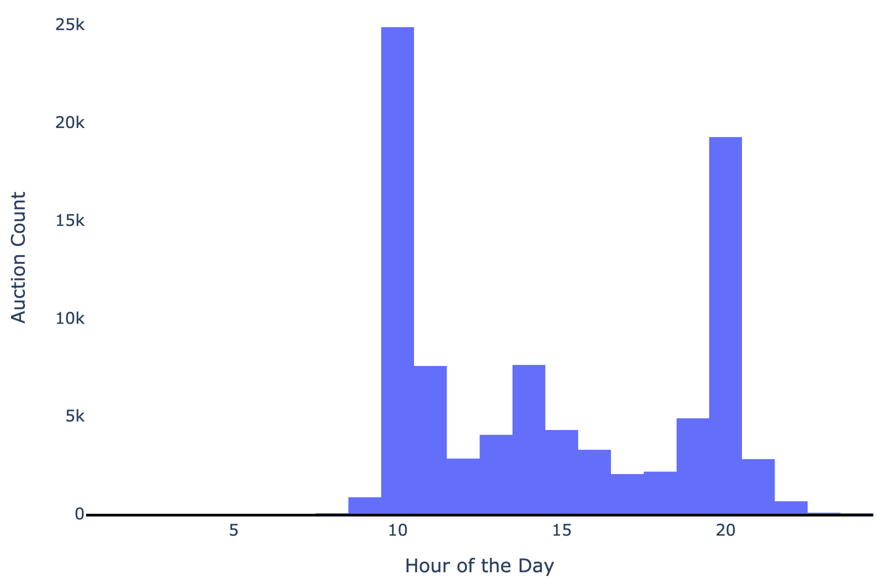
Among the auctions during this period, I drop observations whose data may be erroneous (i.e., the announcement time is later than the actual starting time). After this step, I have 87,169 auctions. I focus on auctions with an ending hour between 9 AM and 10 PM, the most active hours as shown in Figure A.1. After this step, I have 87,054 auctions in total. When recovering the bidders' valuations, I use all 87,054 auctions, as the bids in these auctions are informative about the bidders'

Table A.2: Yearly Distribution of the Commercial Auctions

Year	Number of Auctions	Share in the Whole Sample
2014	26	0.02%
2015	297	0.27%
2016	1,388	1.26%
2017	10,888	9.92%
2018	3,085	2.81%
2019	1,269	1.16%
2020	10,299	9.38%
2021	53,993	49.19%
2022 (five months)	28,528	25.99%

Notes: This table shows the yearly distribution of commercial used-car auctions on Ali Auction. I focus on the period after 2020, which accounts for 85% of all commercial used-car auctions.

Figure A.1: Number of Auctions across Different Hours of the Day



valuations. For seller-side analysis, I focus on the sellers with more than 500 auctions due to three reasons. First, smaller sellers may be occasional users of the platform and hence, may not engage in learning. Second, these smaller sellers may not have enough time to learn about the platform. Hence, their data could not fully reflect how they are learning on the platform. Third, restricting the number of sellers eases the computational burden on the seller side.

In total, 543 sellers list these 87,054 auctions, and 35 firms have more than 500 auctions, accounting for 77% of the commercial auctions (66,780 out of 87,054 auctions). I exclude the largest seller in the sample because the largest seller was banned from the platform as of April 2024 with all auctions and announcements removed due to undisclosed reasons. I further exclude the third and fifth largest firms due to the simple heuristics in choosing the ending hours for the auctions these two firms use. By close examination of these two firms, the two firms are operated by the same manager with the same contact information listed on their announcements. These two firms span their auctions across 9 AM and 10 PM when they have auctions, as shown in Figure A.2. Moreover, the auctions released by these two firms underperform the other sellers as shown in Table A.3. Hence, these two firms are not representative of the rest of the firms, and I drop them for the current analysis. After this adjustment, the set of focal sellers has 32 sellers with 47,472 auctions.

Figure A.2: Number of Unique Hours Chosen by the Excluded Two Firms

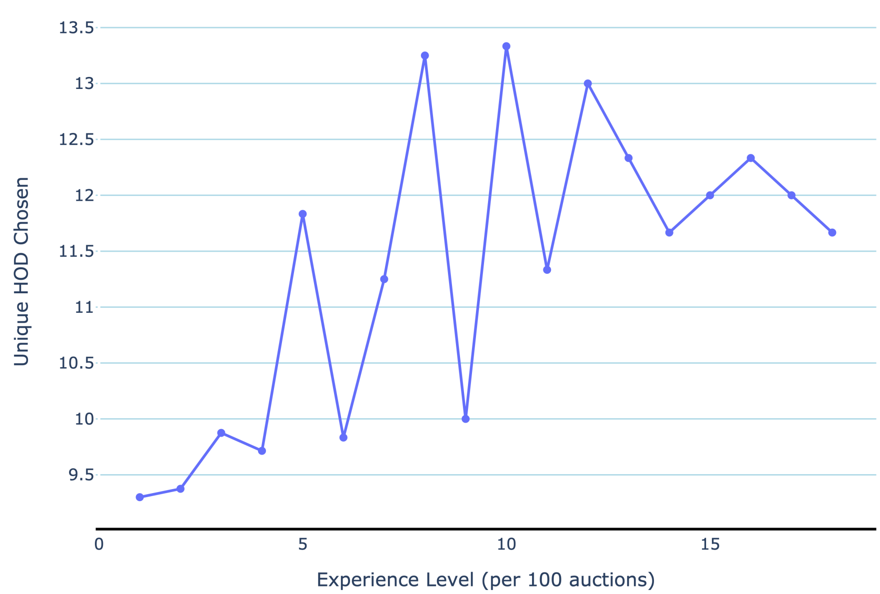


Table A.3: Excluded Two Firms Performance

Group	Selling Prob.	Payoffs (Unconditional)
Excluded	0.26	40,835
Rest	0.66	44,483

Notes: This table shows the comparison between the excluded two firms and the rest of the sellers. The excluded two firms have a substantially lower selling probability and a lower payoff.

B Estimation Details

B.1 Bidder Valuation Details

$$p_1(r) = \frac{\partial}{\partial r} P\left(R \leq r, D_1 = 1\right)$$

$$p_2\left(r, b_{2nd}\right) = \frac{\partial}{\partial b_{2nd} \partial r} P\left(B^{2nd} \leq b_{2nd}, R \leq r, D_2 = 1\right)$$

$$p_3\left(r, b_{2nd}, b_{3rd}\right) = \frac{\partial}{\partial b_{2nd} \partial b_{3rd} \partial r} P\left(B^{2nd} \leq b_{2nd}, B^{3rd} \leq b_{3rd}, R \leq r, D_3 = 1\right)$$

Then, I have the expressions as

$$p_1(r) = \int_{-\infty}^{\infty} \int_{-\infty}^{r-x} F_{U^{2nd} \mid U^{3rd}}\left(r - x \mid u_{3rd}\right) f_{U^{3rd}}\left(u_{3rd}\right) du_{3rd} f_W(r-x) f_X(x) dx$$

$$p_2\left(r, b_{2nd}\right) = \int_{-\infty}^{\infty} \int_{-\infty}^{r-x} f_{U^{2nd} \mid U^{3rd}}\left(b_{2nd} - x \mid u_{3rd}\right) f_{U^{3rd}}\left(u_{3rd}\right) du_{3rd} f_W(r-x) f_X(x) dx$$

$$p_3\left(r, b_{2nd}, b_{3rd}\right) = \int_{-\infty}^{\infty} f_{U^{2nd} \mid U^{3rd}}\left(b_{2nd} - x \mid b_{3rd} - x\right) f_{U^{3rd}}\left(b_{3rd} - x\right) f_W(r-x) f_X(x) dx$$

C Additional Tables

Table C.1: Unique Ending Hours

	Dependent variable:			
	# Unique Hours	# Unique Hours	# Unique Hours	# Unique Hours
	(1)	(2)	(3)	(4)
experience_level	-0.114^{***}	-0.038^{**}	-0.050^{**}	-0.045^{**}
	(0.033)	(0.019)	(0.018)	(0.018)
Seller FE	No	Yes	Yes	No
Tier FE	No	No	Yes	No
Tier x Seller FE	No	No	No	Yes
Observations	550	550	550	550
Adjusted R^2	0.079	0.608	0.613	0.582
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.2: Bidders' and Sellers' Estimation Results

Tier	Hour	μ_u	μ_w	σ_u	σ_w	σ_x
1	9	0.0779	-0.1303	0.4982	0.4880	0.1675
1	10	0.2769	0.0608	0.2668	0.5213	0.2169
1	11	0.1041	-0.0811	0.2190	0.4597	0.2297
1	12	0.1036	-0.1118	0.2684	0.4570	0.2156
1	13	0.3162	0.0487	0.2714	0.4690	0.1993
1	14	0.0225	-0.2130	0.3022	0.5251	0.2364
1	15	0.1904	-0.0783	0.2503	0.5001	0.1868
1	16	-0.0732	-0.3488	0.2179	0.4636	0.2414
1	17	0.0037	-0.1735	0.3063	0.4887	0.1984
1	18	0.3411	0.0202	0.4381	0.6476	0.1715
1	19	0.2302	-0.1230	0.3468	0.6555	0.2438
1	20	0.1706	-0.1381	0.2346	0.5951	0.2419
1	21	0.0454	-0.2194	0.1989	0.5002	0.2457

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Table C.2 – Continued from previous page

Tier	Hour	μ_u	μ_w	σ_u	σ_w	σ_x
1	22	0.1330	-0.0631	0.2546	0.4426	0.1476
2	9	0.1690	-0.0678	0.2613	0.5704	0.1631
2	10	-0.0019	-0.1182	0.2213	0.4189	0.1721
2	11	0.0278	-0.0850	0.2077	0.3923	0.1653
2	12	-0.0014	-0.1504	0.2145	0.4343	0.1634
2	13	-0.0528	-0.2141	0.2526	0.4837	0.1766
2	14	-0.0187	-0.1947	0.2383	0.4818	0.1795
2	15	0.0658	-0.1278	0.1972	0.4429	0.1735
2	16	0.1026	-0.0998	0.2876	0.5295	0.1503
2	17	-0.0342	-0.2975	0.1706	0.4710	0.1980
2	18	0.1681	-0.0996	0.3038	0.5835	0.1507
2	19	-0.0604	-0.2701	0.1959	0.4994	0.1901
2	20	-0.1054	-0.2628	0.1701	0.4434	0.1998
2	21	-0.0142	-0.1433	0.1914	0.3904	0.1707
2	22	-0.0114	-0.1240	0.1828	0.3322	0.1508
3	9	-0.1498	-0.2469	0.2185	0.3207	0.1696
3	10	-0.0673	-0.1058	0.1636	0.2720	0.1740
3	11	-0.1033	-0.1481	0.1851	0.2913	0.1780
3	12	-0.1418	-0.1781	0.2271	0.3424	0.1881
3	13	-0.0699	-0.1220	0.2498	0.3755	0.1435
3	14	-0.0822	-0.2047	0.1926	0.3601	0.1863
3	15	-0.0057	-0.1545	0.1745	0.3948	0.1664
3	16	0.0063	-0.1674	0.1717	0.3989	0.1722
3	17	-0.0329	-0.1944	0.1660	0.3712	0.1731
3	18	0.0270	-0.1900	0.1731	0.4575	0.1513
3	19	-0.1494	-0.3508	0.1816	0.4794	0.1963

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Table C.2 – Continued from previous page

Tier	Hour	μ_u	μ_w	σ_u	σ_w	σ_x
3	20	-0.1048	-0.1800	0.1731	0.3420	0.1564
3	21	-0.0576	-0.1143	0.2003	0.3413	0.1460
3	22	-0.0154	-0.0484	0.2135	0.2724	0.1129
4	9	0.1258	0.0613	0.1460	0.1516	0.1137
4	10	0.1770	0.1398	0.1399	0.1528	0.1648
4	11	0.0142	0.0206	0.2232	0.2507	0.1909
4	12	0.0877	0.0908	0.2414	0.2946	0.1913
4	13	0.0657	0.0224	0.1129	0.2264	0.2179
4	14	0.2847	0.2287	0.1273	0.1994	0.2135
4	15	0.3273	0.2360	0.1160	0.2823	0.2115
4	16	0.3270	0.2422	0.1242	0.2556	0.1851
4	17	-0.0303	-0.0922	0.1432	0.3038	0.2359
4	18	0.0786	0.0073	0.1070	0.2435	0.2458
4	19	0.1344	0.0417	0.1056	0.2999	0.2457
4	20	0.3335	0.2510	0.1260	0.3326	0.2399
4	21	0.5501	0.4446	0.1044	0.3275	0.2055
4	22	-0.0859	-0.1244	0.1723	0.1828	0.2168
5	9	0.2589	0.2275	0.0836	0.0896	0.1563
5	10	0.1892	0.1849	0.1150	0.1045	0.1506
5	11	0.0581	0.1644	0.2050	0.1633	0.1290
5	12	0.0308	0.0913	0.1548	0.1837	0.1206
5	13	0.1314	0.1842	0.0838	0.1605	0.1360
5	14	0.1714	0.2063	0.1051	0.1003	0.1645
5	15	0.1475	0.1783	0.1914	0.1269	0.1507
5	16	0.3724	0.3180	0.1169	0.0808	0.1774
5	17	0.0342	0.1299	0.2625	0.2260	0.1168

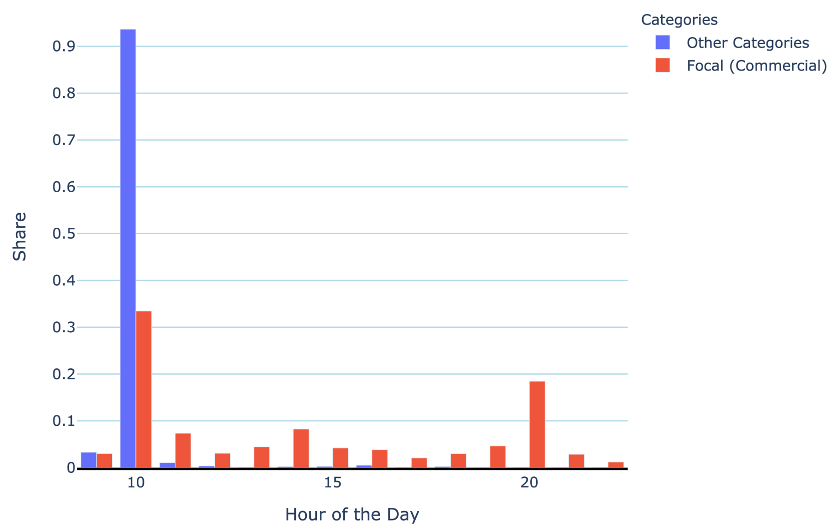
Continued on next page

Table C.2 – Continued from previous page

Tier	Hour	μ_u	μ_w	σ_u	σ_w	σ_x
5	18	0.2166	0.1458	0.1008	0.0995	0.1312
5	19	0.0169	0.1192	0.1690	0.1630	0.1268
5	20	0.0781	0.1386	0.1093	0.1642	0.1335
5	21	0.2602	0.2441	0.0571	0.0830	0.1632
5	22	0.0974	0.1052	0.0804	0.0909	0.1356

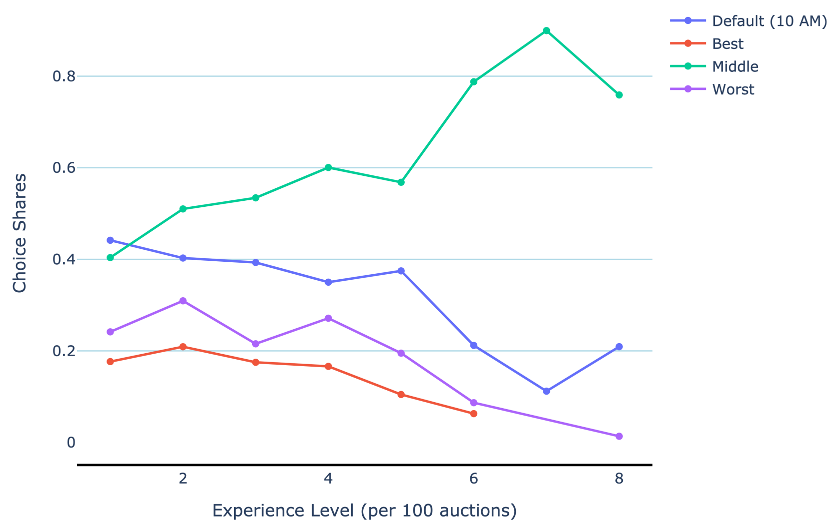
D Additional Figures

Figure D.1: Comparison in Ending Hour Choices across Auction Categories



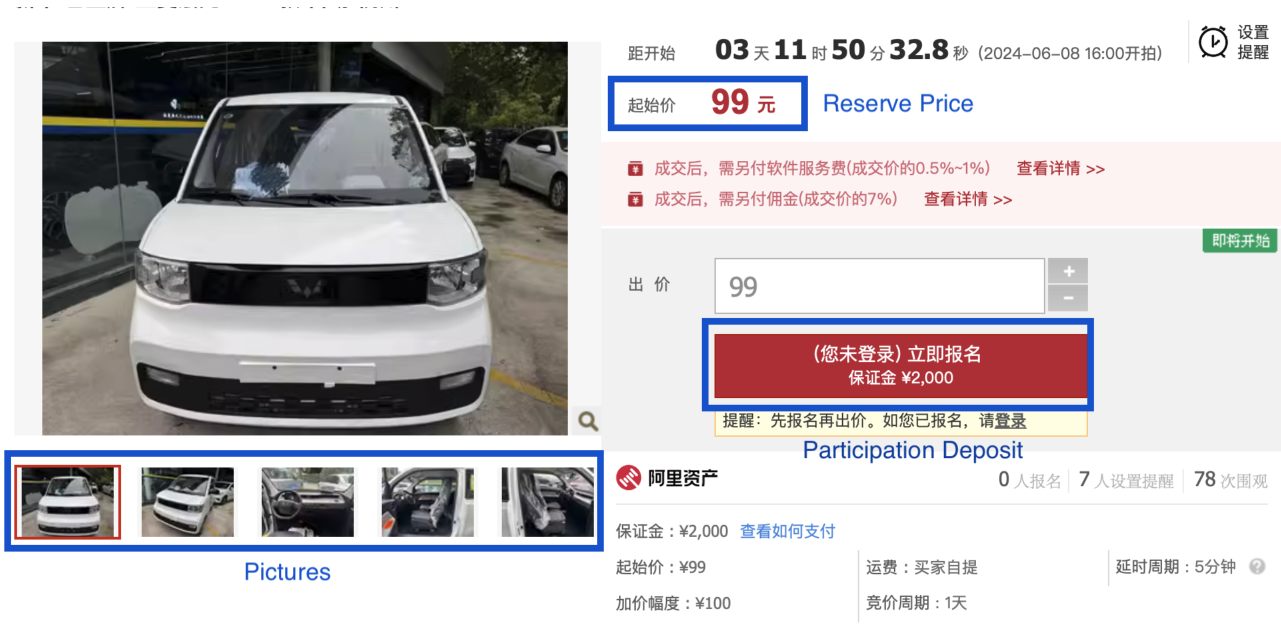
Notes: This figure shows the comparison between the distributions of the ending hour choices between other categories of auctions and the focal category. The x-axis is the hour of the day, and the y-axis is the share of the auctions ending at that hour.

Figure D.2: Shares of Different Hours Chosen



Notes: This figure shows the share of different ending hours chosen by the sellers, averaged across sellers and tiers for a given experience level. The x-axis is the experience level, defined as per 100 auctions. The y-axis is the share of the hours chosen by the sellers.

Figure D.3: An Example of the Auction Page on Ali Auction



Notes: This figure shows an example of the top part of an auction page (i.e., what the bidders will see when they click into the auction) on Ali Auction that is about to start. The pictures, reserve price, and the participation deposit are highlighted by blue rectangles and are in the most visible places.