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Modeling Advertisers' Willingness to Pay in TV Commercial Slot Auctions

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Abstract

Auctions are receiving increasing attention from both practitioners and researchers in the TV advertising market. This paper studies advertisers' willingness to pay (WTP) in Hong Kong television commercial slot auctions, defined as overlapped, multiple-winner auctions with discrete, ascending, semi-sealed bids. We specify advertisers' WTP as a parametric function of their valuations of slot-specific attributes and the valuations that depend on the context of the focal auction and on the competition from other auctions of similar commercial slots. We extend the two "no-regret" bidding principles (first proposed by Haile and Tamer 2003) to obtain informative boundary conditions for asymptotical identification. The estimation results suggest that advertisers' WTP increases with the TV rating of the program in which the advertisement is embedded and decreases with the bidder's bidding experience and the number of similar slot options available. The WTP also depends on the number of bidders classified into the same product category, as two directly competing advertisers are not allowed to advertise in the same commercial break. In the current practice, advertisers submit discrete bids using price levels set by the TV station. Based on the recovered bidder's WTP, we investigate how the TV station can set adjacent price levels and examine the resulting revenue implications.

Keywords: Willingness to pay (WTP); Auction; TV; Advertising; Competition

Introduction

Auctions are becoming prevalent in the TV advertising market. For example, at the end of each year, China Central Television (CCTV) organizes a series of auctions to sell packages of commercial slots embedded in popular TV programs for the coming year. The yearly auction brought CCTV a revenue of 752 million USD in 2015 (Doland 2015). In the US, the Entertainment and Sports Programming Network (ESPN) tried to sell TV ads for its Sports Center highlights shows via web-based "programmatic" auctions in 2015 (Shields 2015). The auction mechanism is also attracting increasing attention from researchers. Typically, the National Broadcasting Company (NBC) in the US sells around 80% of its commercial slots via negotiation in the upfront market before the season starts and leaves 20% of the available slots in the scatter market during the season (Bollapragada and Mallik 2008). Prior research has challenged the efficiency of this commercial slot selling system and suggested new auction mechanisms to increase networks' revenue (Jones and Koehler 2002; Wilbur, Xu, and Kempe 2013). However, empirical research on the traditional television advertising market is rare, mainly due to a lack of available data. In Hong Kong, an auction-like "preemption" system has been in use for more than 20 years. Based on a data set that includes advertisers' commercial slot bidding history at the most popular channel in Hong Kong in 2005, we have a unique opportunity to empirically study advertisers' bidding behavior in TV commercial slot auctions. In this research, we focus on advertisers' willingness to pay (WTP), which is essential in any kind of auction.

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Advertisers purchase commercial slots to broadcast their advertisements. Usually, one commercial break that lasts around 150 s is divided into several slots of unequal lengths. The general practice in Hong Kong is that advertisers bid for each break. Winners with the highest bids are randomly allocated to slots within the break. Thus, a commercial break is considered to be a multi-unit auction[1] in which 1 s is defined as one unit for auction. We define *an advertiser's WTP* as the maximum amount of money the advertiser is willing to pay for 1 s in a commercial break. Advertisers submit discrete bids during the bidding process. The bids are semi-sealed: an advertiser is not able to observe other advertisers' identities or bids. Instead, the TV station observes the entire bidding history and helps advertisers form ascending bids by informing them whether they could win with their current bids and notifying them if and when they are outbid. Several auctions take place concurrently for similar commercial slots; hence, advertisers can participate in more than one auction simultaneously. In terms of the ascending-bid and multiple-auction features, the TV commercial slot auctions bear strong similarities to online product auctions on eBay, Amazon and Yahoo!. Moreover, many researchers have pointed out that bidders' WTP in online auctions is influenced by aspects of the auction environment, such as competition among bidders and items (Bajari and Hortacsu 2003). Similarly, in the television advertising market, advertisers' WTP is also considered to be dependent on auction environmental factors such as advertiser bidding experience and competition among advertisers and commercial slots.

The TV commercial slot auction also differs from online product auctions because of its unique features such as divisible multi-units and discrete semi-sealed bids. Moreover, the auction involves a special source of competition among advertisers within the same product category, because the TV station does not allow two advertisements in the same product category to be aired in the same commercial break (the *anti-competition constraint*)[2] to avoid direct competition between similar products. To summarize, the TV commercial slots are sold in several concurrent multiple-winner auctions. In these auctions, bids are discrete, ascending, and semi-sealed and the bidders face competition at the bidder product category level. Given the uniqueness of this auction practice, it is important to understand: (1) what advertisers' WTP is, (2) how WTP responds to the competition environment, and (3) how the TV station can use its knowledge of WTP to set adjacent price levels to increase the potential revenue. We address these issues in this paper.

In particular, we model bidders' WTP as a parametric function of advertisers' slot-specific valuation, the auction-context-dependent valuation, and the interaction of the two. The slot-specific variables include commercial broadcast time, associated program genres, the TV rating (TVR) of the commercial break, and bidder characteristics such as advertisers' product categories. The context-dependent valuation depends on both the context of the focal auction itself and on competition from other auctions of similar commercial slots. We measure the former by investigating the impact of an advertiser's bidding experience, cumulative expenditure, and competition from bidders in the same product category on bidders' WTP. The latter is captured by including competition measures such as the number of auctions selling similar commercial slots either in or not in the same program within which the focal commercial break is embedded, and the closing price of the latest similar auction.

The paper imposes the least restrictive assumptions on the model. We extend the two general "no-regret" bidding principles, which are originally used in the single-winner English auction (Haile and Tamer 2003), to a multiple-winner auction in which the bids are discrete, ascending, and semi-sealed and bidders face the *anti-competition constraint*. Focusing only on the final bids, the proposed model can be identified asymptotically with informative boundary conditions. Latent bidders are also included in the model.

The model fits the data well. The results show that advertisers in TV commercial slot auctions are willing to pay more when they have spent more in the past, when they are less experienced in bidding, and when it is less possible to find a substitute in other auctions. Based on the estimated results, the TV station can predict its revenue by summing up all of the winning advertisers' predicted WTP in a given period. Furthermore, in the simulation studies, we investigate how the TV station can use its knowledge of WTP to set adjacent price levels and examine the resulting revenue implications. In particular, we try different ways to insert additional price levels in the current price table and vary the incremental size between price levels to assess the resulting changes in the upper bound of the TV station's revenue under new price tables. The results suggest that adding more price levels can increase the upper bound of the revenue, and given limited resources of sales force, it is potentially more profitable to add price levels in the price range in which advertisers have larger surpluses. In addition, the upper bound of the revenue is higher when the TV station decreases/increases the incremental size at lower/higher price levels.

Overall, this paper contributes to the literature of auction design by systematically depicting a new form of auction and proposing an approach to recover bidders' WTP by extending the two general "no-regret" bidding principles to fit this new and complicated auction context. Moreover, the model helps us better understand how advertisers' WTP is related to their slot-specific valuation and to competition from other bidders and other auctions selling similar items. Recovering advertisers' WTP also enables the TV station to rely on the distribution of bidder surplus to improve the pricing scheme, and thus increase potential revenue.

The remainder of the paper proceeds as follows. We first review the literature relevant to television commercial slot auction mechanisms and bidders' WTP in auctions in general. We then introduce the bidding mechanism in the Hong Kong TV advertising market and the data. Next, we develop the

[1] In this paper, (1) the terms "break" and "auction" are used interchangeably, and (2) the terms "advertiser" and "bidder" are used interchangeably.

[2] This is also true in other countries, such as the US (Wilbur, Xu, and Kempe 2013).

model and present the estimation results and managerial implications based on simulation studies. Finally, we conclude with a summary and a discussion of future research.

Literature Review

Previous research has explored various topics in television advertising, yet only a few papers have focused on mechanisms for selling TV commercial slots. In the US, TV stations sell and schedule the majority of their commercial slots mainly via negotiation. Based on the negotiation-based commercial slot selling and allocating system in use at NBC, Bollapragada et al. conduct research to provide better advertisement planning and advertisement scheduling approaches to increase customer satisfaction and the TV station's revenue (Bollapragada et al. 2002; Bollapragada and Garbiras 2004; Bollapragada and Mallik 2008). Other researchers have suggested that bidding is a more profitable mechanism than the negotiation-based system for selling TV commercial slots. Jones and Koehler (2002) design a new combinational auction to sell commercial slots in the upfront market, and Jones and Andrews (2006) discuss the advantages and disadvantages of this combinational auction. Jones and Koehler (2005) and Jones, Easley, and Koehler (2006) further generalize it to more complicated television commercial slot selling contexts. Considering the negative externality among advertisements in the same commercial break, Wilbur, Xu, and Kempe (2013) propose the Audience Value Maximization Algorithm (AVMA) to order candidate advertisements, in which the commercial slot prices are charged via a Vickrey-Clarke-Groves (VCG) auction (Clarke 1971; Groves 1973; Vickery 1961). Following this line of research, the purpose of our paper is to empirically study advertisers' bidding behavior with a focus on advertisers' WTP in TV commercial slot auctions.

Little research has been done on advertisers' WTP in TV advertising auctions. However, the commercial slot auctions discussed in this paper bear some similarities to online product auctions, which have garnered significant attention from researchers. On the one hand, product attributes and bidder characteristics have been shown to affect bidders' WTP (e.g., Chan, Kadiyali, and Park 2007; Yao and Mela 2008). On the other hand, many researchers find that in online auctions that include several concurrent auctions selling similar items, bidders' WTP also depends on the auction environment, because it influences each bidder's expectation of other bidders' valuations (Bajari and Hortacsu 2003). Yao and Mela (2008) develop a structural model to infer buyers' latent valuations in online auctions. Their results show that in addition to item and seller characteristics, auction characteristics are one of the main factors that affect buyer valuations. The impact of the auction context on bidders' WTP depends on the characteristics of the focal auction, including bidder experience (Goes, Karuga, and Tripathi 2010; Srinivasan and Wang 2010), budget constraints (Borle, Boatwright, and Kadane 2006), and the number of persuasive messages issued by the auction owner (Ducarroz, Yang, and Greenleaf 2016), and on competition from other concurrent auctions that sell similar items, including market depth, market breadth, and the closing prices of these auctions (Chan, Kadiyali, and Park 2007; Pilehvar, Elmaghraby, and Gopal 2016). Additionally, the current number of bids, the bidding time, and pre-auction estimates are important auction context factors that influence bidders' dynamically updated WTP in ascending auctions (Dass 2011). These studies provide a sound theoretical ground for modeling advertisers' WTP in TV advertising auctions.

To recover advertisers' WTP, we have to link the unobserved WTP to observed bids. Because bidders may use various bidding strategies in ascending auctions, there is no one-to-one correspondence between unobserved WTP and observed bids. Haile and Tamer (2003) propose two general bidding principles based on no-regret rules to estimate bidders' WTP in English auctions. Haile and Tamer (2003) show that these simple principles enable them to construct informative bounds on bidder valuations in a nonparametric approach. They further argue that the two principles are consistent with the utility maximization framework under general conditions and many equilibrium bidding behavior assumptions, such as in Milgrom and Weber's (1982) "button" model. This approach is safe and efficient even when the data-generating process deviates from the assumptions in restrictive models. Hortaçsu and McAdams (2018) prove that in open-outcry auctions, the upper and lower bounds on the distribution of bidder values can be identified from the distribution of the final price if bidders use no-regret bidding strategies. In multiple online notebook English auctions, Chan, Kadiyali, and Park (2007) apply the two principles to model bidders' WTP with a parametric function approach. They point out that asymptotic identification can be achieved with parametric assumptions for distributions of unobserved variables in the WTP and enough randomness in bidders' bidding strategies. In this paper, we apply the two "no-regret" bidding principles to a first-price ascending auction with discrete semi-sealed bids, multiple winners and competition across advertisers from the same product category.

The Hong Kong TV Commercial Slot Selling Mechanism and the Data

In this section, we first introduce the TV commercial slot selling mechanism in Hong Kong and summarize the sample data to motivate the model. We then examine advertisers' bidding patterns in the data section to prove the validity of applying the two "no-regret" bidding principles in our auction context.

The Commercial Slot Selling Mechanism

Advertisers broadcast their advertisements during TV commercial breaks. One commercial break can be divided into several slots of unequal lengths. Each advertiser takes one slot. The general practice in Hong Kong is for advertisers to commit to spending a certain amount on advertising with the TV station for the entire coming year at the end of the previous year. The actual amount spent must be greater than or equal to the committed amount. Before the commercial break air time, advertisers privately communicate with the TV station to specify which commercial break they want, how many seconds they plan to purchase and how much they would like to pay for 1 s. Without observing other bidders' identities or bid amounts, an advertiser is informed by the TV station whether its submitted price is high enough to obtain a slot, that is, whether its price is currently one of the highest prices submitted for that commercial break. If this is the case, this advertiser is temporarily assigned a random slot in the specified commercial break. Preemption allows a temporarily assigned slot to be recalled from one buyer (Advertiser A) and be reassigned to another buyer (Advertiser B) with a higher bidding price. In this example, Advertiser A is preempted by Advertiser B.[3,4] The TV station will inform Advertiser A once he or she is preempted, but will never provide detailed information about Advertiser B's identify or bid amount. Advertiser A can reschedule to a similar slot in another break with the same price, resubmit a higher price to get the slot back or give the slot up altogether. This preemption can happen at any time before the commercial slot broadcast day at no cost.[5] At the end of the preemption, the advertisers who finally obtain the slots have to pay their named prices.[6] Because 1 s of commercial airtime equals one unit on offer, a commercial break can be considered a divisible discriminatory multi-unit auction in which bidders have multiple-unit demands.

This multi-unit auction allows advertisers to get slots in the same break at different prices. The prices bid for a given commercial break may vary across advertisers due to their different intrinsic valuations of the commercial break, which could be linked to factors such as how significant the impact of TV advertising is on sales in the product category the advertiser belongs to, the match between the advertiser's target customer group and the audience for the TV program the ad is embedded in, and how strongly the advertiser wants to win the auction. In addition, advertisers with less bidding experience may submit higher bids, as they may have less experience in evaluating the competition level in the auction.

During the bidding process, a given advertiser does not observe other advertisers' identities or price levels. However, the TV station assists advertisers in forming ascending bids by informing them whether they could win with their current bids and notifying them if and when they are preempted by other advertisers. Via the private communication with the TV station, an advertiser can infer the price level it needs to outbid. Therefore, the bids in these auctions are semi-sealed. Moreover, the bids submitted are not continuous variables. Instead, the TV station provides 14 ascending price levels from which advertisers can choose.[7] An advertiser is required to bid at least one price level higher than the incumbent winner to preempt it. This feature is equivalent to requiring advertisers to submit discrete bids with predefined increment levels at the current winning price. Increments at different price levels vary because the monetary differences between two adjacent price levels are not the same. Therefore, a commercial break is a discriminatory multi-unit auction with discrete semi-sealed bids.

The auction starts when slots become available for purchase and ends one day before the broadcast day. We assume that all of the bidders make daily bidding decisions. Because Hong Kong TV stations start selling commercial slots for the coming year at the end of the preceding year (e.g., selling for 2005 started on December 17, 2004), all of the auctions start on the same day but close on different days depending on the broadcasting date. Because of this characteristic, auctions are overlapped, so that an advertiser can participate in more than one auction at the same time. Furthermore, advertisers compete fiercely with each other in the product market. According to the *anti-competition constraint*, two advertisements in the same product category (as classified by the TV station) cannot be aired in the same commercial break. Therefore, advertisers face competition from bidders both within and across product categories. The above-listed auction features make the TV commercial slot selling mechanism unique.

The Data

Program and bidder attributes. The commercial slot selling data in this paper are provided by the largest local TV station in Hong Kong. Our sample covers the slot bidding history of the most popular channel in the first quarter of 2005. The TV station divides all of its commercial airtime into seven time classes according to their expected popularity. Airtime between 2:10 and 7:00 am is in the lowest time class, while airtime between 6:50 and 11:00 pm on weekdays is in the highest class. For different time classes, the same price level corresponds to different monetary values. Advertisers are charged a larger monetary amount for slots in higher time classes. Our research focuses on commercial breaks in the highest three time classes, which cover prime time, when preemption occurs most frequently. In addition, the TV station

[3] In practice, advertisers can be preempted for reasons other than higher bids. For example, a special ad from the local government can occupy any given slot at any given time. However, we focus only on preemption due to higher bids, as such preemptions represent about 90% of all preemptions in real operations.

[4] This could be the case if, e.g., Advertiser B's ad lasts 15 s while Advertiser A's ad lasts 30 s. In this case, the TV station would cut the length of the commercial break by 15 s. Note that shortening this commercial break does not necessarily lead to a loss of profit, because the Hong Kong government specifies that the maximum commercial time in 1 hour is 10 minutes. Therefore, the TV station could allocate the 15 s to another commercial break in the same hour.

[5] The preemption may stop several days before the slot is broadcast if the incumbent advertisers bid high enough. Because this situation is not common in practice, we consider the preemption ending time of all auctions to be the day before the broadcast day.

[6] The monetary amounts advertisers pay are equal to their announced prices per second multiplied by the advertisement durations.

[7] According to the amounts they commit to spending on advertisements in the coming year, advertisers are assigned different ranks and hence get different rates of quantity discounts at these fixed price levels. That is, bidding at the same price level, an advertiser with a larger commitment amount could actually pay less than an advertiser with a smaller commitment amount. All of the WTP values measured in this paper are translated into the actual money amounts advertisers will pay. This feature also increases the randomness in advertisers' bids.

Table 1
Summary statistics.

Variables	Mean	sd
Slot attributes		
Commercial break TV rating	22.16	8.54
Bidder characteristics		
Total number of bids	73	151
Total number of wins	30	42
Total advertising expenditure (million HKD)	4.04	6.6
Number of bidders in the same product category	5	4
Focal auction characteristics		
Number of observed bidders per auction	11	6
Number of winners per auction	6	3
Mean winning price per auction (HKD)	6,483	3,118
Competition measures		
Number of similar auctions in the same program (depth)	7	4
Number of similar auctions in different programs (breadth)	6	6
Closing price of similar auction (HKD)	6,396	3,206

classifies all advertised products into 766 categories. The sample data include advertisements in 178 product categories. Note that a firm could advertise multiple products in more than one product category. Because a given firm has separate marketing and advertising teams for different product categories, and different teams may even hire different advertising agencies for their TV commercials, we consider a firm-product category to be one bidder in this research. Thus, in our paper, different product categories belonging to the same firm are distinctive bidders and each bidder belongs to one and only one product category.

After we eliminate 4.98% of the records due to raw data input errors, the sample data set consists of 1,953 breaks, 405 bidders, and 17,096 break-bidder level observations. Table 1 presents the summary statistics. Among 80 programs in the sample, the most popular program genre is drama. Around 40% of the commercial breaks in the sample occur during dramas. In addition, 43.85% of the advertisements are aired during commercial breaks between two different programs. An average commercial break lasts around 176 s and includes 6 advertisements. The average TVR of the commercial breaks[8] in the sample is 22.16, with a standard deviation of 8.54.

Table 1 shows that in each bidder's product category, the number of active bidders during the sample period ranges from 1 to 20, while the average value is 5. To capture bidder heterogeneity in our model, we group the 405 bidders into four broad product categories: food and clothing, services (such as restaurants and local telephone networks), household (such as tissues and air fresheners), and others, accounting for around 18.0%, 35.3%, 35.3%, and 11.4% of the total sample, respectively. In addition, their average per-second winning prices are 7,209 HKD, 8,628 HKD, 7,963 HKD, and 7,122 HKD, respectively.

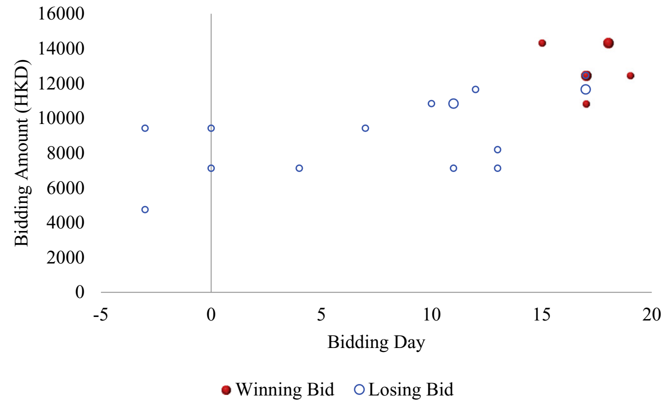

Fig. 1. Bidding history for a break on January 25, 2005. Note: Day 1 refers to January 1, 2005. Day 5 refers to December 26, 2004.

Bidding patterns. In a divisible multi-unit auction, more than one bidder could win with different bids. On average, there are 11 bidders and 6 winners in an auction. The mean winning price across auctions is 6,483 HKD per second with a standard deviation of 3,118 HKD. In the sample period, an average advertiser submits 73 bids (with sd 151) and wins 30 (with sd 42) slots with an advertising expenditure of 4.04 (with sd 6.6) million HKD. Table 1 also provides the summary statistics of competition measures among overlapped auctions, whose specific definitions are discussed in the model section. On average, for a focal auction, there are 7(6) auctions selling similar commercial slots embedded in the same program (different programs) during the sample period. In addition, the mean closing price of concurrent auctions selling similar commercial slots is 6,396 HKD per second.

To better understand advertisers' bidding behavior, we plot the bidding history (including both winning bids and losing bids) for a commercial break embedded in a popular drama program broadcast from 10:08 to 11:03 pm on January 25, 2005. In Fig. 1, the x axis is the bidding day counting from the first day of 2005, while the y axis is the bidding amount in HK dollars. The hollow circles represent losing bids, while the solid circles represent winning bids. For both hollow circles and solid circles, the size of the circle represents the number of bids at the same point (bidding day, bidding amount). For example, two winning bids are submitted on Day 18, each for an amount of 14,334 HKD. In the 225-s commercial break, 18 bidders participate and 7 bidders eventually win.[9] Most bidders submit only one bid, and the maximum number of bids per bidder is 3. The mean bidding amount is 10,473 HKD (with a standard deviation of 2,623 HKD). Bidders begin to submit bids for this commercial break 25 days before the broadcasting time and

[8] In the data, we observe program TVR—program audience size expressed as a percentage of the population, rather than commercial break TVR. Because watching TV is a passive leisure activity and the zapping rate during commercials is usually low (Anand and Shachar 2011), we let the TVR of a within-program commercial break be approximately equal to the TVR of the program in which it is embedded and let the TVR of a between-program commercial break be equal to the average TVR of the two neighboring programs.

[9] Two bidders win on day 17 with a bidding amount of 12,464 HKD, and two bidders win on day 18 with a bidding amount of 14,334 HKD.

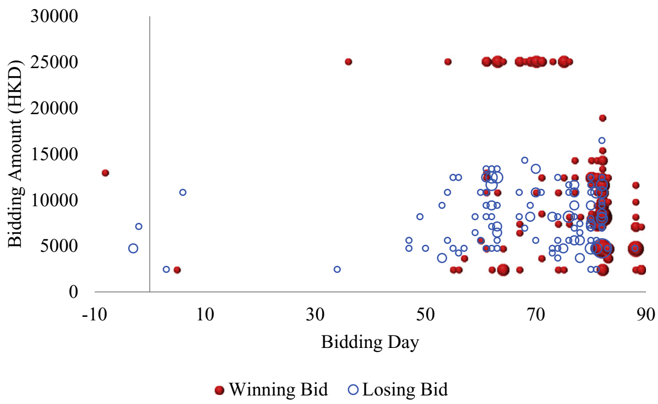

Fig. 2. Bidding history for 23 breaks on March 31, 2005. Note: Day 1 refers to January 1, 2005. Day 10 refers to December 21, 2004.

continuously submit ascending bids throughout the bidding period.

Similarly, in Fig. 2, we plot the bidding history for all 23 breaks on the last day of our sample: March 31, 2005. The majority of the bids start about one month before the broadcasting day of the commercial breaks and continue throughout the following bidding period. In all, 85 bidders submit 254 bids in these auctions. On average, a bid is submitted 19 days before the auction ends. The mean bidding amount is 9,383 HKD (with a standard deviation of 5,602 HKD). We also check the bidding history for other individual breaks and for breaks on the last day of the month in January and February and observe a similar pattern: bids are spread throughout the bidding period. In the sample as a whole, more than 90% of the bids are submitted 3–15 days before the commercial broadcasting day. This indicates that the bidders in our sample seldom exhibit sniping behavior. That is, bidders seldom wait to submit bids toward the end of the auction, which is crucial for our application of Haile and Tamer's (2003) two bidding principles.

The Model

The WTP Function

Suppose that there are H (h = 1, 2, ⋯, H) auctions or commercial breaks and I (i = 1, 2, ⋯, I) active bidders in the sample period. Only N_h bidders submit bids in auction h. The bids are dependent on bidders' WTP per second for a given auction. Based on the advertisement durations, bidders request slots that consist of different units or seconds during a particular commercial break. Because the number of units an advertiser requests is essentially fixed at the advertisement duration level once the advertisement has been created, regardless of the bidding process, we do not account for advertisers' quantity decisions in this research. All of the WTP values discussed in the paper are measured at the second level. This also allows us to compare the WTP for bidders with different advertisement durations. In addition, we assume that advertisers treat all slots or units as identical in auction h because advertisers can choose only which break to bid on and their specific ad positions are randomly allocated by the TV station. The WTP of bidder i for auction h is unobservable to the TV station and researchers. We model it as a parametric function of the observed variables.

In TV commercial slot auctions, advertisers' WTP depends not only on their valuations of the slot, but also on the auction environment. Let π_{ih}^1 capture the valuation generated from the slot. We then define the auction-context-dependent valuation as being affected by the focal auction context (π_{ih}^2) and by competition from other auctions selling similar commercial slots (π_h^3). In addition, interactions between slot-specific valuation and auction environments may also influence WTP. For example, different advertisers may have different responses to their bidding experience. The valuation of commercial slots embedded in special programs is less affected by competition from auctions of similar slots. We adopt a multiplicative form of the slot-specific valuation and two types of context-dependent valuations for advertisers' WTP to capture the interaction effects between slot-specific valuation and auction environments. We follow Chan, Kadiyali, and Park (2007) to assume that bidder i's WTP in auction h, W_{ih}, have the following parametric functional form:

$$\ln(W_{ih}) = \overline{\pi}_{ih} + \varepsilon_{ih} = \pi_{ih}^1\left(1 + \pi_{ih}^2 + \pi_h^3\right) + \varepsilon_{ih}, \quad (1)$$

where $\overline{\pi}_{ih}$ stands for the deterministic part of the WTP. The random error term is assumed to follow an i.i.d. normal distribution: $\varepsilon_{ih} \sim N(0, \sigma_\varepsilon^2)$. The log of WTP is taken to guarantee that a positive value is generated from the right-hand side of Eq. (1).

Slot-specific valuation—auction independent. We specify, π_{ih}^1, the bidder's auction-independent valuation of the slots in auction h, as a function of the slot attributes, the bidder characteristics, and their interactions. Because all slots in auction h are treated as identical, we use break-level attributes such as the break time class, the log of the break TV rating and whether the break is embedded in the most popular program genre (drama) to measure the slot attributes. Because a high time class value is assigned to the time zone with a high TVR and our parsimonious simple regression results suggest that the time class has a linear effect on the observed bids (Long and Freese 2006), we enter the time class variable with ordinal values into the model as a single variable instead of creating K-1 (with K denoting the number of total time class levels) dummy variables.

To capture the impact of bidder characteristics, we consider product categories of bidders according to their advertised products. Bidders from different product categories may have different preferences for program genres and time classes, as they target different audience groups. For instance, children's toy manufacturers whose main customers are young children may prefer cartoons in the afternoon or early evening (a lower time class) to late-night dramas (a higher time class), while skincare product companies targeting professional women may prefer late-night dramas. Therefore, we let the valuation also depend on the interaction between the bidder product category and the associated program genre (whether the associated program genre is a drama) and the interaction between the bidder product category and the break time class. As described earlier, to make the estimation manageable, we group the 178 product categories into four broad product categories: food and clothing, services, household, and others, and examine the impact of the broad product category on bidders' slot-specific valuation. To further capture the unobserved heterogeneity, we also include the unobserved bidder-specific characteristic ϵ_i, which is i.i.d. normally distributed across bidders: $\epsilon_i \sim N(0, \sigma_\epsilon^2)$, and the unobserved slot attribute τ_h, which is i.i.d. normally distributed across breaks: $\tau_h \sim N(0, \sigma_h^2)$. The bidder's slot-specific valuation π_{ih}^1 could then be specified as

$$\pi_{ih}^1 = X_h' \times \alpha + \epsilon_i + \tau_h, \tag{2}$$

where X_h is a vector of the aforementioned variables and vector α is the collection of the corresponding parameters to be estimated. The variances of unobserved random variables ϵ_i and τ_h also need to be estimated.

Context-dependent valuation I—focal auction dependent. An advertiser's valuation is also influenced by the bidder's status in the focal auction. Let π_{ih}^2 denote the valuation that depends on the context of the focal auction only:

$$\pi_{ih}^2 = Y_{ih}' \times \beta, \tag{3}$$

where Y_{ih} collects four focal auction context variables, and β is a four-by-one column vector of the corresponding parameters to be estimated. In particular, we include bidder i's cumulative number of bids and cumulative number of wins prior to the focal auction h to capture the impact of bidders' bidding experience on WTP. Past research has documented that bidders update their valuations based on their bidding histories and adjust their subsequent bidding strategies when participating in overlapping auctions that sell similar items (Hossain 2008; Srinivasan and Wang 2010). The third variable included is bidder i's cumulative expenditure prior to auction h, which indirectly reflects bidder i's bidding strategy. All of these three variables are log-transformed and take the form of log (1 + y) when entered into the model. To capture the impact of the competition level corresponding to the bidder product category, we also include the total number of bidders who are in the same product category as bidder i and are active in the sample period. The value of this variable is inherent and independent of the specific auction. However, it is determined by the auction design—how the TV station classifies advertisers into different product categories—and it directly affects the competition level in the focal auction due to the *anti-competition constraint*. Thus, we consider this variable to be one source of context-dependent valuation in the focal auction.

Context-dependent valuation II—competition from other auctions selling similar slots. Chan, Kadiyali, and Park (2007) show that market competition is another important influence on bidders' WTP. In overlapping auctions, bidders face a large number of similar concurrent auctions. We define similar auctions of the focal auction as auctions that sell commercial slots (a) in the same time class, (b) in the same program genre, (c) within the range of ±2 days of the broadcasting day, and (d) within ±2.5 deviations of the TVR_h of the commercial slots in the focal auction. The effect of competition from other similar auctions is then specified as

$$\pi_{ih}^3 = Z_h' \times \gamma, \tag{4}$$

where Z_h is a collection of variables that measures the competition from other similar auctions, and γ is a three-by-one column vector of corresponding parameters. We first investigate the impact of market depth and market breadth on bidders' WTP. The market depth is measured by the number of type I similar auctions that sell similar commercial slots in the same program in which the focal commercial break h is embedded, while the market breadth is measured by the number of type II similar auctions that sell similar commercial slots that are *not* in the same program in which the focal commercial break h is embedded. In our definitions, the items counted for market depth and market breadth are mutually exclusive, so that we are able to distinguish the impact of these two types of similar auctions on the bidders' WTP. Moreover, we measure the closing price (the average winning price weighted by the duration of the advertisement in the auction) of the most recent similar auction that ends before auction h. The log of this variable is also taken to enter into the model. It is defined as equal to the average closing price of all of the other concurrent similar auctions if no similar auctions precede the focal auction h.

The Two Bidding Principles

In an ascending first-price auction, it is not necessary for the observed final bids to be exactly equal to the bidders' WTP. However, the range of WTP can be inferred from the observed bids. Haile and Tamer (2003) propose two "no-regret" bidding principles to construct informative boundaries for the WTP in a nonparametric model:

1. Bidders do not bid more than they are willing to pay.
2. Bidders do not allow an opponent to win at a price they are willing to beat." (v0).

Chan, Kadiyali, and Park (2007) apply the two principles to model bidders' WTP using a parametric approach. Haile and Tamer (2003) show that the two bidding principles are consistent with general equilibrium assumptions. The first principle is true in any ascending first-price auction in which any bid a bidder submits could be what the bidder has to pay and thus should be lower than the WTP. The validity of the second principle requires that the bidders be capable of observing and responding to their competitors' bids when they are outbid. The second principle is not valid in hard ending online auctions, such as eBay auctions, in which bidders frequently snipe; that is, bidders strategically submit their bids toward the end of the auction. Sniping is less likely to occur in TV commercial slot auctions for the following two reasons. First, the necessity of offering bidding prices taken from a discrete price level menu provided by the TV station and the large difference between adjacent price levels gives advertisers an incentive to submit bids early to increase their chances of winning the auction. For example, suppose the WTP of both advertiser A and advertiser B is between two adjacent price levels (say, Level 7 and Level 8), and thus neither advertiser will bid higher than Level 7. The advertiser who first bids at Level 7 could win the slot, as it cannot be preempted by the other advertiser, whose WTP is less than the next price level. Second, one major reason for sniping is that bidders are afraid of revealing their valuations through their early bids. Unlike open ascending auctions, in which all bidding information is released to the public, the semi-sealed feature of the bidding mechanism considered here can greatly mitigate advertisers' concerns about valuation disclosure. Figs. 1 and 2 in the data section also provide strong empirical evidence to rule out sniping in our sample. Instead of springing up on the last day of the auction, more than 90% of the bids are spread between 3 days and half a month before the auction ends.

Another important concern for the validation of the second principle is that bidders may collude so that the losers' WTP may be higher than the winning bid. During the bidding process, the semi-sealed auction design prevents bidders from knowing the identities or bidding prices of the other participants, which makes collusion difficult. Although bidders are able to identify competitors after the commercial break is aired, and thus are able to collude in subsequent auctions of commercial slots, lacking information on competitors' bidding prices could largely reduce bidders' incentive to collude. Furthermore, in addition to bidders from its own product category, a bidder also competes with bidders from other product categories who are bidding for the same commercial break. This adds to the complexity of collusion among bidders of the same product category. To examine potential collusive behavior across bidders empirically, we treat bidders within the same product categories as direct competitors and examine their bidding histories in the most popular drama broadcast during the sample period. We select the top three product categories in terms of the number of bids submitted for breaks during the drama and focus on the largest two bidders in each category. We count the competition as occurring once if both bidders submit bids for the same commercial break. In all of the three product categories, the frequency of competition is not decreasing across the broadcasting day, indicating no significant evidence of two competing bidders in the same product category using historical information to collude to avoid direct competition for the same breaks. In addition, among all commercial breaks embedded in the drama, we find that around half include bids submitted by more than one bidder from the same product category, and the number of such breaks is not decreasing across the broadcasting day (0.012, p-value = 0.403). Overall, in our data, we do not find significant evidence of collusive behavior across bidders.

Furthermore, our conversations with managers from the TV station suggest that there may be coordination across product categories of the same firm at macro level, following the overall marketing plan of the firm, but not at the auction level. In our data, there is also no significant evidence of collusion across different product categories of the same firm at auction level, since 706 out of 1,953 commercial breaks in our sample include advertisements from different product categories of the same firm. Taken together, these empirical investigations further guarantee the validity of the second bidding principle in our context.

To fit the specific auction context in this paper, we further modify the second principle as follows. First, in TV commercial slot auctions, advertisers are required to choose from the discrete fixed price levels provided by the TV station. To win the auction, the new bidder must bid at least one price level higher than the incumbent bidder. In other words, the bidders submit bids in fixed increments. The discrete feature of the observed bids does not affect the generalizability of principle 2. With fixed price levels, bidders face the additional constraint of a minimum increment, which is equal to the difference between a higher price level and the current price level. Principle 2 could be modified to state: “No bidder will stop bidding as long as its WTP exceeds the incumbent's price plus the minimum increment” (v1).

Second, previous research has applied the two bidding principles only to auctions with a single winner. In the discriminatory multi-unit auctions discussed in this paper, multiple winners win the same auction at different prices. The new bidder can win the auction as long as its bid is one level higher than the current lowest price level in the same commercial break. Principle 2 then needs to be further modified to state: “No bidder will stop bidding as long as its WTP exceeds the lowest winning price plus the minimum increment” (v2). Unlike bidders in ascending first-price auctions or in the English auction context, bidders in commercial slot auctions cannot observe other bidders' bidding histories. However, bidders can infer the current lowest winning price via their direct communication with the TV station about whether they can enter their bids at a certain price level. Hence, the advertisers can follow the above-modified second principle.

Finally, two advertisements in the same product category are not allowed to air in the same commercial break. To win the auction, the new bidder must bid one price level higher than the incumbent winner in the same product category, if there is such an incumbent. In this case, bidding higher than the lowest winning price level is no longer enough to win the auction. Taking the above issues into account, the two bidding principles can be finally modified to state:

1. No bidder bids more than its WTP.
2. No bidder will stop bidding as long as its WTP exceeds the weakest rival winner's winning price plus the minimum increment. If there is an incumbent winner in the same product category as the new bidder, the new bidder's weakest rival winner is that incumbent winner; otherwise, the weakest rival winner is the bidder who wins with the lowest bid (v3).

Without competition at the product category level. The above two bidding principles allow us to estimate bidders' WTP based only on their observed final bids. We start with the case in which two ads in the same product category are allowed to air in the same break. The two principles of v2 are applied in this case. Suppose there are N_h observed bidders and M_h winners in auction h. Without a loss of generality, we assume that the first M_h bidders win the auction in descending order according to their observed final bids and the M_h^{th} winner places the lowest bid. On the one hand, all of the winners' bids should be no more than their own WTP:

$$W_{ih} \geq b_{ih}; i = 1, 2, \ldots M_h, \tag{5}$$

where b_{ih} is bidder i's final bid in auction h.

On the other hand, all of the losers' WTP should be equal to or larger than their own bids and smaller than the lowest winning bid in auction h plus the minimum increment:

$$b_{ih} \leq W_{ih} \leq b_{M_h h} + \Delta_{M_h h}; i = M_h + 1, \ldots, N_h, \tag{6}$$

where b_{ih} is bidder i's final bid in auction h, $b_{M_h h}$ is bidder M_h's final bid in auction h, and $\Delta_{M_h h}$ is the minimum increment associated with the lowest winning price level in auction h. Different increments correspond to different price levels.

With competition at the product category level. Since two ads in the same product category cannot be aired in the same commercial break, only one advertiser in each product category can win in each auction. The above boundary conditions for winners remain the same, while some modifications are required for losers.

For loser i, if there is no winner in the same product category, the condition in (6) still holds. However, if there is a winner denoted by s in auction h who is in the same product category as loser i, then bidder i drops out of the auction as long as its WTP is less than the winner s′ s actual bid plus the minimum increment. Thus, the following condition should be satisfied:

$$b_{ih} \leq W_{ih} \leq b_{sh} + \Delta_{sh}; i = M_h + 1, \ldots, N_h, \tag{7}$$

where Δ_{sh} is the minimum increment associated with the winner s′ s price level in auction h.

The above two conditions can be further integrated into one:

$$\begin{aligned} & b_{ih} \leq W_{ih} \leq (b_{sh} + \Delta_{sh})^{\eta_{ih}} (b_{M_h h} + \Delta_{M_h h})^{(1-\eta_{ih})}; \\ & i = M_h + 1, \ldots, N_h, \end{aligned} \tag{8}$$

where the indicator η_{ih} = 1 if there is a winner s in auction h who is in the same product category as loser i; otherwise, η_{ih} = 0.

Latent Bidders

Some bidders may be interested in an auction, but do not ultimately submit a bid in that auction. Chan, Kadiyali, and Park (2007) point out that although latent bidders are not observed in the data set, the estimates could be biased if they are ignored. There are many possible reasons for bidders to stay latent. For instance, latent bidders' WTP could be lower than the lowest observed bid in the auction. Alternatively, bidders may be inactive in the focal auction even if their WTP is high because, for various reasons, they are waiting for an opportune moment to enter (Chan, Kadiyali, and Park 2007). Among different options, we use the least restrictive assumption for latent bidders, assuming that their WTP is less than the highest winning price plus the minimum increment:

$$W_{ih} \leq b_{1h} + \Delta_{1h}, \tag{9}$$

where W_{ih} is bidder i's WTP for auction h, b_{1h} is the highest winning price in auction h, and Δ_{1h} is the corresponding minimum increment. Similar to Chan, Kadiyali, and Park (2007), we identify latent bidders by their participation in competing auctions that sell similar slots. To construct a reasonably sized set of latent bidders, we define latent bidders as those who submit no bids in the focal auction but bid at least twice in auctions that are (a) in the same time class, (b) in the same program genre, (c) within the range of ±2 broadcasting days, and (d) within ±1 deviation of the TVR_h of commercial slots in the focal auction.

Estimation and Identification

Based on the parametric function of WTP and the informative boundary conditions induced from the two bidding principles, we derive the log-likelihood function as follows:

$$LL = \log \int \prod_{h=1}^{H} \left\{ \prod_{i=1}^{M_h} \left(1-\phi\left(B_{ih}^1\right)\right) \cdot \prod_{i=M_h+1}^{N_h} \left(\phi\left(B_{ih}^2\right)-\phi\left(B_{ih}^1\right)\right) \cdot \prod_{i=N_h+1}^{L_h} \phi\left(B_{ih}^3\right) \right\} dF(\epsilon_i, \tau_h), \tag{10}$$

where

$$B_{ih}^1 = \left(\log(b_{ih}) - \overline{\pi}_{ih} \right) / \sigma_\varepsilon,$$

$$B_{ih}^2 = \left[\log\left((b_{sh} + \Delta_{sh})^{\eta_{ih}} (b_{M_h h} + \Delta_{M_h h})^{(1-\eta_{ih})} \right) - \overline{\pi}_{ih} \right] / \sigma_\varepsilon,$$

$$B_{ih}^3 = \left(\log(b_{1h} + \Delta_{1h}) - \overline{\pi}_{ih} \right) / \sigma_\varepsilon.$$

Notation $\phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. Given the unobserved bidder-specific effect ϵ_i and the slot attribute τ_h, each observed bid follows a truncated normal distribution. The first part in the brackets denotes the likelihood of all winners' bids in auction h, and the second part represents the likelihood of all losers' bids in auction h. Supposing that there are L_h bidders including latent bidders in auction h, then the last part in the brackets measures the likelihood of latent bidders' bids. Chan, Kadiyali, and Park (2007) show that the model is asymptotically identifiable when we impose parametric assumptions on unobserved distributions and with enough randomness on bidders' strategic behaviors. In our model, all of the unobserved factors are assumed to follow normal distributions to determine the point estimate of the WTP. We also observe enough randomness in bidders' bidding strategies in multiple winner auctions. For example, bidders can adopt different bidding strategies, such as waiting and jumping. Some patient bidders may wait and gradually increase their bids in small increments. Bidders may also choose to bid high enough at an early stage to avoid being preempted. Additionally, because the bids are semi-sealed and winners pay what they bid, a winner with a lower bid may have a higher WTP than another winner with a higher bid. Therefore, the difference between bid and WTP varies across bidders. With sufficient variation in our data, we use the Maximum Simulated Likelihood (MSL) approach to estimate the proposed model. The unobserved bidder-specific effect ϵ_i and the slot attribute τ_h are integrated out.

Validation Check

As we discussed in the above section, the advertisers' final bids are not precisely equal to their true WTP in our auction settings. The required increment with fixed price levels further enlarges the discrepancy between an observed bid and the estimated WTP. Therefore, it is inappropriate to directly compare each bidder's observed bid and estimated WTP. To make model checking feasible but still valid, we regress the mean of all of the observed winning bids of auction h ($\overline{bid_h}$) on the mean of the highest M_h^{th} (the number of observed winners in auction h) predicted WTP ($\overline{\widehat{WTP}_{ih}}$) in distinct product categories[10]:

$$\overline{bid_h} = \rho \cdot \overline{\widehat{WTP}_{ih}} + \xi_h \tag{11}$$

where ξ_h is the random error term. The requirement of distinct categories is established to be consistent with the fact that only one bidder in the same product category is able to win in an auction. We use the Monte Carlo simulation method to generate 500 draws for all of the unobserved variables in the WTP function to calculate the estimated WTP of all of the bidders (including latent bidders) in each auction h. Rank all advertisers in descending order in terms of their estimated WTP and select the first M_h^{th} estimated values from advertisers in distinct categories to calculate the $\overline{\widehat{WTP}_{ih}}$ for the regression test. The estimated ρ is 0.855, which is significant and close to one. The adjusted R-square is 0.888, indicating a good model fit.

The above procedure is also useful for the TV station to predict revenue. In particular, the TV station could apply our proposed model to the target period, simulate the WTP of all bidders in each auction according to the estimation results and use eq. (11) to predict the mean unit price in each auction. Multiplying the predicted mean unit price by break duration, we could obtain the predicted advertising spending for each auction. The final predicted revenue is the sum of the predicted advertising spending of all of the auctions.

Table 2
Estimation results.

	Observed Bidders Only (N = 17,096)		Latent Bidders Included (N = 29,352)		Elasticity
	Estimates	sd	Estimates	sd	
Constant	8.294	0.055	7.904	0.041	
Slot-specific valuation					
Program genre (drama)	0.311	0.125	0.140	0.077	−4.235
Time class	0.159	0.071	0.251	0.048	−0.508
Ln(TVR)	−1.360	0.154	−1.625	0.108	0.506
Bidder type					
Food and clothing	2.792	0.857	2.388	0.447	−6.732
Service	1.937	0.507	2.101	0.338	3.639
Household	1.200	0.500	1.953	0.349	6.570
Interaction of program genre with bidder type					
Drama*Food and clothing	−0.192	0.159	−0.061	0.096	1.813
Drama*Service	−0.325	0.150	−0.111	0.089	3.334
Drama*Household	−0.275	0.148	−0.164	0.088	4.988
Interaction of time class with bidder type					
Time class*Food and clothing	−0.442	0.132	−0.344	0.068	0.700
Time class*Service	−0.422	0.085	−0.353	0.054	0.720
Time class*Household	−0.305	0.082	−0.337	0.055	0.687
Context-dependent valuation I (Focal auction context effects)					
Ln(cumulative bids + 1)	0.052	0.003	0.029	0.002	−0.096
Ln(cumulative wins + 1)	−0.011	0.002	−0.002	0.002	0.007
Ln(cumulative expenditure + 1)	−0.015	0.001	−0.010	0.001	0.035
Ln(number of bidders in the same product category)	−0.010	0.002	−0.013	0.001	0.047
Context-dependent valuation II (Market competition effects)					
1/(depth + 1)	0.009	0.009	−0.129	0.008	−0.054
1/(breadth + 1)	0.009	0.004	−0.0001	0.003	0.00003
Ln (closing price of similar auctions)	−0.135	0.002	−0.138	0.002	0.505
Error variances					
ϵ_i (bidder specific)	0.684	0.024	0.112	0.013	
τ_h (auction specific)	0.973	0.022	0.026	0.012	
σ_ε (bidder and auction specific)	0.542	0.006	0.443	0.004	
Negative log likelihood	13,518.83		18,971.59		
BIC	13,630.91		19,089.89		

Note: The dependent variable is ln(WTP). The elasticities are measured for the variables before being mathematically transformed.

Results

Table 2 reports the main estimation results.[11] The results in column 2 and column 3 are estimated from the model that includes observed bidders only. The results in column 4 and column 5 are obtained from the model that includes both observed and latent bidders. The results of most of the main variables from both models are similar in both sign and magnitude. The following discussion is based mainly on the results from the model that includes latent bidders. In this model, there is larger heterogeneity across bidders (0.112) than across auctions (0.026). Because the model is nonlinear in parameters, to clearly understand how bidders' WTP changes with respect to the change in explanatory variables (before any functional transformation), we report the corresponding elasticities in column 6. The elasticity of a continuous variable is

[10] Both of the means of the observed and predicted winning bids are weighted averages by slot duration. The slot duration for a latent bidder is unobserved in the data, so we let it be equal to the mode value of all of the bidder's purchased slots in the sample data.

[11] To check the robustness, we split the broad category of food and clothing into two separate categories and re-estimate the model. Similar results are obtained.

measured as the percentage change in bidder WTP when the value of the explanatory variable increases by 1%, while the elasticity of a binary dummy variable is counted as the difference of bidder WTP when it equals one versus when it equals zero, ceteris paribus. All elasticities are first numerically evaluated for each observation and then averaged for the mean effects. A positive value of the elasticity indicates a positive impact of the explanatory variable on bidders' WTP.

As expected, a higher TVR induces a higher valuation of the slot and thus a higher WTP (0.506). On average, the bidders are willing to pay an extra 196 HKD[12] for one TVR point increase per second. In terms of advertiser product categories, the advertisers for food and clothing have a much lower WTP (−6.732) than do advertisers in other product categories, while the WTP of advertisers in the household product category is the highest (6.570). The commercial airtime during dramas is most valued by sellers of household products (4.988) and is least appreciated by food and clothing providers (1.813). Unlike baseline bidders who sell other types of products (−0.508), the bidders selling food and clothing, services, and household products prefer slots broadcast in a higher time class (at night rather than in the afternoon) when more viewers are able to watch TV (0.700, 0.720, and 0.687).

We also find that the auction environment significantly affects advertisers' WTP. All of the context variables of the focal auction have significant estimates except the cumulative number of wins. The results show that more experienced bidders have a lower WTP (−0.096). The bidders have a higher WTP if they have spent more in past auctions (0.035). One possible reason is that bidders who have bid high in the past tend to maintain an aggressive bidding strategy throughout the sample period. Moreover, competition within the same product category enhances bidders' WTP (0.047). On average, a bidder's WTP increases by 90 HKD when one additional bidder is assigned to its product category. We discuss this issue further in the next section.

The bidders' WTP is also affected by competition from other auctions selling similar slots. The results show that the closing price of a similar auction in the preceding bidding period is positively correlated with bidders' WTP in the focal auction (0.505). The WTP in the focal auction increases by 0.67 HKD with a 1 HKD increase in similar auctions' closing price. In several overlapping auctions, competition and price increases easily spread to other similar auctions because bidders are allowed to switch among auctions without significant transaction costs. The WTP in the focal auction is negatively correlated with market depth (−0.054), while its correlation with market breadth is insignificant. This suggests that the competition comes mainly from auctions in the same program. In other words, when advertisers lose in the focal auction, they are more likely to bid for another commercial slot in the same program instead of looking for a substitute in a different program. The bidders' WTP is lower when there are more alternative options. To reduce the cannibalization effect among auctions in the same program, it is important for the TV station to provide a large variety of programs, given the fixed total program broadcasting time.

Simulation Studies

In the TV commercial slot auctions, advertisers bid at 14 discrete price levels offered by the TV station. Advertisers obtain the surpluses that are equal to the discrepancies between their final bids and WTP. Based on the WTP recovered by our proposed model, we can estimate the surplus for each advertiser. Overall, advertisers have captured a surplus of 285 million HKD, which is around 17.7% of the total advertising revenue or 15% of the total WTP generated by TV commercial slot auctions during our sample period. This indicates a large room for the TV station to extract more bidder WTP.

Discrete price levels may extract more or less surplus from the WTP, depending on the distribution of the WTP. Compared to the current pricing scheme, setting a bigger jump between two adjacent price levels may help the TV station to extract more WTP from the winning bids given the requirement to outbid the bids below, or it could eliminate more competitors and make the market less competitive; and vice versa. The overall effect is an empirical question. In this section, we conduct simulation exercises to investigate how the TV station can use its knowledge of advertisers' WTP to set adjacent price levels and examine the resulting revenue implications. The following two exercises are provided: (1) adding more price levels to the current 14 discrete price levels which results in smaller intervals between adjacent price levels where new price levels are inserted, and (2) varying the incremental size at lower and higher price levels while keeping the total number of price levels unchanged. We evaluate the impact of these new price tables on the upper bound[13] of the TV station's revenue, which is the sum of all bidders' highest possible bids (lower than but closest to the WTP).

Adding More Price Levels

We calculate the surplus for each winning advertiser using its winning price and the recovered WTP. We then aggregate the surplus across advertisers at each price level to get the distribution of the size of the surplus across the 14 price levels. For each pair of adjacent price levels, we insert one price level at the middle point of the adjacent price levels while holding the rest of the price table constant. We calculate the upper bound of revenue for the TV station given the new price table and measure the percentage change relative to the upper bound of the revenue in the current price table. We repeat the process

[12] This value is equal to the corresponding elasticity multiplied by the ratio of the mean WTP and the mean TVR of the entire sample. The same calculation is also applied to the other explanatory variables discussed in the following analysis.

[13] We are not able to obtain the point estimate of the price level each bidder submits under the new price table hence are unable to estimate the resulted revenue for the TV station. A structural that models bidders' bidding strategy in equilibrium is required for achieving this, which is beyond the scope of this paper. We acknowledge this as the limitation of this paper.

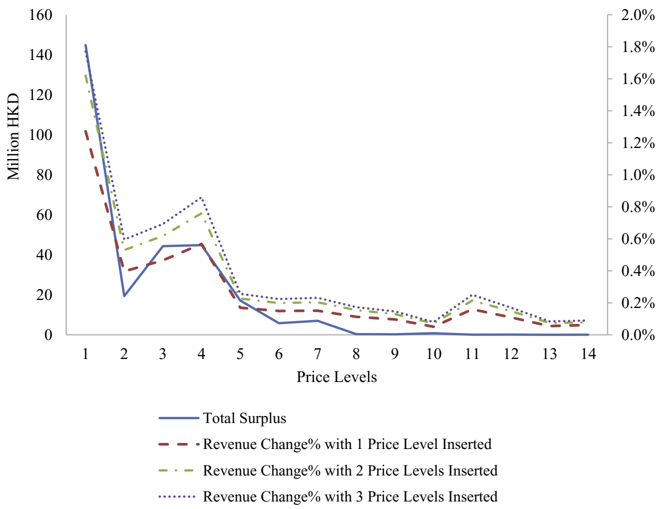

Fig. 3. Total surpluses and change percentages in the upper bound of the revenue across price levels. Notes: The vertical axis on the left is the amount of total surplus in terms of million HKD, while the vertical axis on the right is the change percentage. The horizontal axis is the price level.

for each pair of adjacent price levels and present the total surpluses and change percentages resulted from the 14 new price tables in Fig. 3. The thick dashed line plots the revenue change percentages across these price tables. Results across all 14 resulted new price tables suggest that adding a price level increases the upper bound of the revenue, with the size of the increase larger in the price range with higher advertiser surplus.[14]

Next, we insert more price levels for each pair of adjacent price levels and calculate the impact of the resulting new price table on revenue change. In Fig. 3, the dot-dashed line and the dotted line plot the percentage change in the upper bound of the revenue when adding two price levels (at 1/3 and 2/3 quintiles) and three price levels (at 1/4, 2/4, and 3/4 quintiles), respectively. Similarly, the revenue increases are higher when more price levels are inserted in the price range with more advertiser surplus. In addition, adding more price levels induces a larger increase in the revenue upper bound. In the current practice, all bids are made via private communication with the sales force of the TV station. Adding too many price levels may increase the TV station's operating cost. Given limited resources of sales force, it is more profitable to add price levels in price ranges in which advertisers have larger surpluses.

The above simulation exercise adds price levels to one pair of adjacent price levels while holding the rest of the price table unchanged. We further examine the potential revenue impact of inserting price levels at multiple pairs of adjacent price levels. Starting from the pair that generates the highest revenue increase, we sequentially insert one price level at the middle point of two adjacent price levels following the descending order of the size of the revenue increase. The result is presented in Fig. 4. As Fig. 4 shows, the marginal benefit of adding one

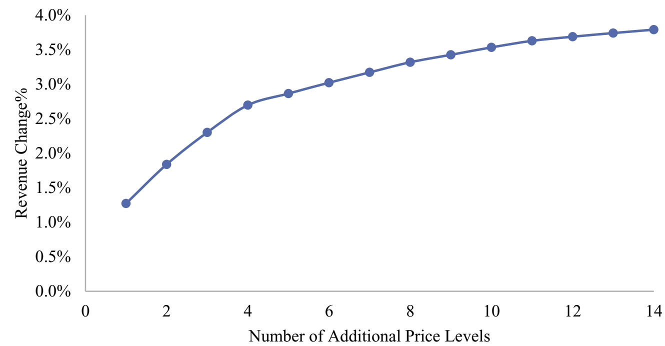

Fig. 4. Change percentages in the upper bound of the revenue across price levels.

more price level at another pair of adjacent price levels decreases. If we add 14 price levels simultaneously, the upper bound of the revenue is raised by 3.79%. Considering that more price levels may incur more operating costs, the TV station should select the optimal number of price levels to add by leveraging the potential profit increase and additional operating costs incurred.

Changing the Incremental Size

Considering the interval between zero and the first price level to be the first price interval, there are 14 price intervals in the current price table. Keeping the total number of price levels and the highest price level constant, we change the size of 7 pairs of price intervals by adding Q HKD to each of the first 7 price intervals while deducting Q HKD from each of the last 7 price intervals. We vary the amount of Q from −700 to 700 with 100 as the incremental size.[15] Excluding the case that Q is equal to zero in which nothing is changed, there are 14 different values for Q and thus 14 different new price tables. Under each new price table, we calculate the upper bound of the TV station's revenue and measure the percentage change relative to the upper bound of the revenue under the current price table. Results are presented in Fig. 5.[16] The results suggest that decreasing the incremental size at lower price levels while increasing the incremental size at higher price levels leads to a positive change in the upper bound of the TV station's revenue; and vice versa. In addition, the change percentage of the upper bound of the revenue reaches the maximum point when the change of the price intervals is equal to 400 HKD. The results suggest that given the distribution of bidders' WTP in our sample data, decreasing/increasing the incremental size at lower/higher price levels may lead to potential revenue increase for the TV station.

In the above simulation exercises, we modify the price table by adding price levels or changing the incremental size between different price levels to examine their impacts on the upper

[14] The total surplus of bidders at price level 8 or above is much smaller relative to the total surplus obtained at price level 1. One important reason is that much fewer advertisers win at these price levels.

[15] In the current price table, the lowest increment between two adjacent price levels is 812 HKD.

[16] We have changed the incremental size of the first and last 6 and 5 price intervals and find similar patterns.

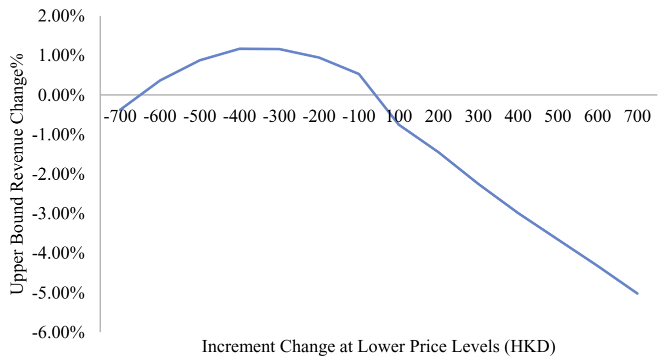

Fig. 5. Change percentages in the upper bound of the revenue when changing the incremental size of the first 7 and last 7 price intervals. Notes: The vertical axis is the percentage change in the upper bound of the TV station's revenue under the new price table. The horizontal axis is the change (in HKD, measured by Q) in the incremental size at lower price levels.

bound of the TV station's revenue. The upper bound provides insight on the extent to which the TV station can achieve in its revenue. Note that the change in the upper bound of the revenue does not necessarily leads to a proportional change in the TV station's actual revenue, which also depends on advertisers' bidding strategies under the new price table. For example, the actual revenue would be closer to the upper bound when the majority of the advertisers bid aggressively and frequently jump, but farther from the upper bound when the majority of the advertisers bid conservatively and often gradually increase the bid. In practice, the TV station may make inferences about the distribution of advertisers' bidding strategies based on their bidding histories or other external information sources.

Conclusions

With a unique and rich data set, this paper empirically studies advertisers' WTP in TV commercial slot auctions. These auctions are overlapped auctions with a complex bidding mechanism, in which the bids are discrete, ascending, and semi-sealed and multiple bidders can win in the same auction with different bids. Based on research on online product auctions, which bear many similarities to our auctions, we specify advertisers' WTP as a parametric function of the slot-specific valuation and auction-context-dependent valuation from both the focal auction and other auctions of similar slots, and their interactions. We capture bidder heterogeneity by allowing interactions of slot attributes and bidder type and including unobserved bidder-specific characteristics. Next, we conduct boundary estimation by extending the two “no-regret” bidding principles (Haile and Tamer 2003) to capture the specific auction form in our context. Latent bidders are included for a more accurate estimation. The way we model the WTP is also applicable to other auctions that share similar features, such as the semi-sealed auctions discussed by Teich et al. (2001).

The results suggest that bidders' WTP in commercial slot auctions is affected by slot attributes, bidder characteristics and variables pertaining to the auction environment. Our model estimation results provide revenue insights that are critical for TV stations with demand uncertainty. Based on the recovered bidder WTP, we find that the overall level of bidder surplus is around 17.7% of the total advertising revenue in the sample period, which indicates a large room for the TV station to extract more bidder WTP. In the simulation studies, we propose different discrete price levels for advertisers to bid and examine the resulting revenue change of the TV station. We find that given limited resources of sales force, it is potentially more profitable to have more price levels in the price range in which advertisers have larger surpluses. In addition, the TV station can potentially achieve a higher revenue when it decreases the incremental size at lower price levels and increases the incremental size at higher price levels.

Several interesting avenues could be explored in future research. First, although it is an important contributing factor to WTP, the program TVR is not ex ante observed by advertisers during the bidding process, so we use the ex post realized program TVR as a proxy. In the real bidding process, advertisers predict the program TVR from the TVR histories of similar programs and the target program information provided by the TV station. Resolving the uncertainty of TVR in a stochastic bidding process could be an interesting research area in the future. Moreover, the TV station faces the important question of how to design the auction price table. In the current study, we are not able to provide point estimate of the price levels advertisers submit under new price tables and hence the TV station's revenue as we do not explicitly model their bidding strategies in equilibrium. In our simulation exercises, we examine the impact of different price tables on the upper bound of the TV station's revenue. In future research, a structural model that explicitly models advertisers' bidding strategies could help investigate specific bidding outcomes, and thus the point estimate of the revenue given different price tables. However, the equilibrium solution in the structural model depends on the validity of assumptions exerted on the model. Our current approach is less restrictive to these assumption hence is more flexible and feasible to practitioners.

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