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Design of a Combinational Auction Mechanism for Television Advertising Market in Taiwan

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Abstract: The lack of a transparent mechanism makes the television advertising market in Taiwan extremely volatile to supply and demand changes. To resolve the problem, this study suggests a transparent and fair auction mechanism for the TV advertising market. A characteristic of television commercials is that there exists a synergy between time slots of commercials, i.e., it is more effective for advertisers to acquire some time slots together than just to obtain one of them. A combinatorial auction mechanism is proposed, which enables the advertisers to bid for a set of time slots simultaneously, thus avoiding the problem of losing any item in the bidder desired bundle. This study models the TV commercial combinatorial auction as an integer programming problem. One-month time slots of a TV channel in Taiwan are used in a computational experiment. The problem is solved by LINGO 12.0 and the resulting solutions provide a satisfactory allocation of time slots and maximize revenue for the TV station.

Keywords: Combinatorial auction, exposure problem, integer programming, television advertising market

INTRODUCTION

Among all advertising media in Taiwan, television is the first choice for advertisers. Cable TVs together with TV networks have accounted for 50% of the total advertisements since 2009 and the number is still growing (Optimum Media Direction, 2010). The price of a TV commercial is the dynamic result of the competition between supply and demand under a free market mechanism and fluctuates cyclically with the dull/rush seasons. However, following a sudden boom in Taiwan TV advertising market in 2009, the situation has changed. The price of buying an advertising time slot of the TV station was raised three times within a day. Though prior agreement on the price had already been made, the media agency had to accept the new price set by the TV station or its commercial would be dropped. Such an unreasonable price change also posed difficulty for the media agencies to communicate with their customers (i.e., advertisers). This chaos in the campaign market was due to a serious imbalance between supply and demand as pointed out by the chairman of the Media Agency Association in Taiwan, who emphasized the need for a new market mechanism to deal with the pricing problem so as to maintain the efficiency of the market because he expected that the dull and rush seasonal cycle might no longer be as regular as it was Chiu (2010).

To resolve the price chaos in Taiwan TV advertising market, experts suggested establishing an auction mechanism that provides a transparent pricing and contracting system for both the TV station and the media agencies (Chiu, 2010). However, it is noted that a regular single-item auction mechanism may not meet the needs of this industry. The advertisers generally require more than one time slot to place their commercials and these time slots are of different shows on different days. Thus, a multiple-item auction would be more appropriate for the TV advertising market. The two traditional types of multiple-item auction are sequential auction and parallel auction. In a sequential auction, the items are auctioned one at a time Boutilier *et al*. (1999), Hausch (1986) and Sandholm (2000). Bidding in a sequential auction is difficult if the bidders have preferences over bundles. To determine his valuation for an item, the bidder needs to estimate what items he will receive in later auctions. This often leads to inefficient allocations where bidders fail to get the combinations they want and instead get the ones they do not. Such a difficulty is referred to as the *exposure problem*, which occurs when the buddle preferred by the bidder has a synergy over its individual items. De Vries and Vohra (2003) illustrated this problem with an extreme example of a bidder who values the bundle of goods *i* and *j* at $100 but each separately at $0. In the sequential auction, this bidder may have to submit high bids on *i* and *j* to secure them. If he loses the bidding on *i*, then he is left standing with a high bid *j* which is of no value to him. On the other hand, in a parallel auction (Hausch, 1986), the items are open for auction

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simultaneously; bidders may place their bids on multiple items during a certain time period and the bids are publicly observable. In this type of auction, the uncertainty and the need for looking ahead is not as drastic as that in a sequential auction, because a bidder can roughly speculate the courses of other bidders' bids according to the revealed information. However, the parallel auction still suffers from the exposure problem.

Combinatorial auctions can be employed to overcome the need of looking ahead and the inefficiencies that stem from the related uncertainties (DeMartini *et al*., 1998; McMillian, 1994; Rassenti *et al*., 1982; Sandholm, 1993). In a combinatorial auction, there are one seller (or several sellers acting in concert) and multiple bidders. The bidders may place bids on combinations of items, allowing a bidder to express complementarities between items. Thus, he does not have to speculate on an item's valuation under the impact of possibly not getting other complementary items. The winner determination problem in combinatorial auctions is an NP-complete problem (Sandholm, 2000). Thus, the feasibility of applying combinatorial auctions to real-world problems had been debated (McMillian, 1994). For example, combinatorial auctions had been considered by the Federal Communications Commission (FCC) since 1993 for the auction of spectrum rights (Bykowky *et al*., 2000). However, the winner determination problem is intractable for such an auction design at that time, so the plan was pending. To resolve the computational complexity of combinatorial auctions, Rothkopf *et al*. (1998) and Park and Rothkopf (2001) limited biddable combinations and thus the winner determination problem can become computationally manageable with some restriction strategies that allow bids on what may be economically sensible combinations.

In 2008, the FCC formally adopted the combinatorial auction for selling the 700-MHz radio spectrum rights by utilizing the tree structure suggested by Rothkopf *et al*. (1998) to constrain the number of biddable combinations and obtained $19 billion revenue for the American government. Another successful implementation of combinatorial auctions is the school meal catering contract assignment in Chile (Epstein *et al*., 2002). The government of Chile spent $180 million/year on school meals for 1.3 million children from low-income families. To improve the quality of the assignment, the authority adopted the combinatorial auction for assigning catering contracts. An integer linear programming model was constructed to decide contract awards optimally among different concession holders. The resulting solution improved the price quality ratio of the meals with yearly savings of around $40 million.

Though combinatorial auction has not yet been applied to TV advertising market in the real world, a simulation by Jones *et al*. (2006) showed its potential in efficient allocation of commercial resources. The auction mechanism used in the simulation is called rule-based combinatorial auction (Jones and Koehler, 2002), which allows bidders to describe their audience rating targets by rules. Such rules enable advertisers to specify the desired viewing rate of a certain audience group or the preferences of time slots to place their commercials. Jones and Koehler (2002) modeled the TV advertising rule-based combinatorial auction as an integer programming problem with the objective of maximizing revenue for the TV channel under the constraint of the rules submitted by bidders. In the model of Jones and Koehler (2002), the TV channel not only determines the winning bidders but also the exact time spot allocations, which generally demands a great deal of computation. In the example provided by their study, there are 325 bidders and 24 shows containing 587 commercial time units and such a case results in 278,000 binary variables and 587,000 constraints. It is also noted that the above case only deals with the primetime shows in one week; thus, the computational demand will be even more intensive if the whole set of shows in a longer period is considered.

In Taiwan, the schedule of shows of a TV channel generally changes each month and thus it would be appropriate to assume that the bidding of commercial time slots is on a monthly basis. The exact slot of a commercial is determined right before the show starts, so it is not necessary to make such a decision in the stage of determining winning bids. In other words, if we consider each show as an item and all time slots of the show are identical units of the item, then the time slot allocation problem becomes a multi-unit combinatorial auction, which has been discussed by Gonen and Lehmann (2000) and Leyton-Brown *et al*. (2000). Currently, the TV channels in Taiwan offer buddle selling of commercial slots that divides the time of a day into many tiers, e.g., tier of primetime or tier in the early morning. It is easy for a TV channel to sell out all commercial slots of primetime shows, but not so easy for the time slots in the very early morning even though they are much cheaper. Buddle selling provides combinations of a time slot in the primetime tier with that in other unpopular tiers and offers a price that is lower than the sum of the prices of individual time slots in the bundle. Such type of buddle selling was not considered in the model of Jones and Koehler (2002).

To resolve the price chaos of TV advertising market in Taiwan, this study suggests a combinatorial auction mechanism based on the concept of rule-based combinatorial auction of Jones and Koehler (2002). Considering the time-slot bundling selling practice in Taiwan, we incorporate the bundle selling option in the auction mechanism. This combinatorial auction process is modeled as an integer programming problem and solved by optimization software. The feasibility and performance

of the proposed approach are evaluated by numerical simulations with data generated from a real-world case.

COMBINATORIAL AUCTION MECHANISM

There are two major selling methods in the TV advertising market in Taiwan, namely spot buy and CPRP buy. Spot buy means that the advertiser specifies the exact show/time he likes to place his campaign. The type of bundle selling mentioned in the previous section can also be considered as a spot buy. CPRP stands for *cost per rating point*, which is the cost of advertising divided by the viewing rate of the advertisement. CPRP buy guarantees that the target Gross Rating Point (GRP) specified by the advertiser will be reached in a certain period. In other words, the advertiser does not need to specify the time slots and the TV channel will arrange all possible slots to satisfy the GRP requirement. In the television industry, the measurement of viewing rate is generally obtained via the reports by the television audience measurement company, AGB Nielsen. CPRP buy is less expensive than spot buy, because the TV channel generally uses as many time slots of unpopular shows as possible to satisfy the advertiser demand. In CPRP buy, the advertiser can specify multiple audience groups and their individual target GRPs. In our model, such requirements will become the constraints of problem formulation.

As mentioned in the previous section, the TV channels in Taiwan provided a bundle selling of time slots. Table 1 illustrates an example of time tiers of a TV channel, where Tiers A, B and C represent three different time intervals, respectively. The shows in Tier A attract more audiences and hence, the price of advertising is higher, while placing an advertisement in shows of Tier C is less expensive because the audiences are fewer during that time. It is noted that the price of a tier combination is less than the sum of individual tiers in that combination. For example, a 10 sec slot in Tier A costs $1500 and that in Tier C costs $300, but buying these two slots together would cost $1600 only. Such bundle selling serves to encourage advertisers to purchase the time slots that are less attractive. The campaign time slots of a TV channel can be considered as perishable goods; thus it is crucial for the TV channel to sell out all the time slots before the show starts.

The bundle selling prices in Table 1 are list prices and are negotiable depending on the bargaining power of the media agency. To incorporate the idea of promoting unpopular time tiers in our model, we propose using virtual money to reward the bidders who demand time slots in an unpopular tier. Suppose a bidder requests a 10 sec slot in Tier A and a 10 sec slot in Tier C with a bid price of $1500. To reward this bidder for choosing a time slot in Tier C, the TV channel endows him with $200 virtual money and thus the bidder price becomes $1700, which enhances his competiveness in the auction.

Table 1: Example of time tiers in a day

Tier	Time	Price per 10 sec
A	18:00-01:00	$1500
B	07:00-18:00	$800
C	01:00-07:00	$300

A + C: $1600; A + B: $19000; A +B + C: $19100

Table 2: Example of CPRP buy target

Audience group	Target GRP
Female, age 18-49	155
Female, age 25-54	155
Male, age 18-49	145
Male, age 25-54	145
Adult, age 18-49	165
Adult, age 25-54	165

In our auction mechanism, bidders are allowed to do spot buy by specifying the shows they like to place their campaigns, or they can also specify the shows they do not want their campaigns to appear. For CPRP buy, bidders can describe the audience groups and their target viewing rates. Table 2 demonstrates an example of the desired GRP of different viewing groups.

In the proposed auction mechanism, we suggest a single-round sealed-bid auction. The bid submitted by a bidder contains descriptions of desired/undesired shows as well as the audience groups and their GRP targets along with a bid price. The auctioneer (i.e., the TV channel) will endow virtual money to the bid if it is applicable and then determine the winning bids by solving an optimization problem, which will be presented in the next section.

PROBLEM FORMULATION

A show generally contains five to ten commercial breaks referred to as pods and a pod contains five to ten 10 sec slots. The base unit of allocation in this auction is the 10 sec slot (referred to as *unit* hereafter) and if the advertiser demands a commercial longer than 10 sec, then he will need to bid for multiple 10 sec slots in a show. Each show is considered as an item and all the 10 sec slots are identical units of that item. Thus, in our mechanism, we are dealing with a multi-unit combinatorial auction problem.

As mentioned in the previous section, the proposed auction mechanism suggests using virtual money to encourage the purchase of time slots in unpopular time tiers. Let c_s be the virtual money per unit associated with show s and $l_{b,s}$ be the length (in units) of the bidder campaign; thus, if show s is demanded by bidder b, the original bid price of bidder b (i.e., p_b) will be adjusted as:

$$p'_b = p_b + \sum_s c_s l_{b,s} h_{b,s}, \forall b \quad (1)$$

where, $h_{b,s}$ denotes the intention of bidder b and $h_{b,s} = 1$ means that bidder b demands show s and 0 otherwise. The objective of the TV channel is to maximize his revenue after adjustment:

$$\text{Maximize} \sum_b p'_b y_b$$

where, y_b is the decision variable of the TV channel and $y_b = 1$ if bidder b has a winning bid and 0 otherwise.

Let $x_{b,s}$ be the decision of the number of time units allocated to bidder b, then the relation between $x_{b,s}$ and the total length of time (in units) the campaign appearing in the show will be:

$$x_{b,s} = l_{b,s,} k_{b,s} \forall b, s \tag{2}$$

where, $k_{b,s}$ is the number of times the bidder campaign appearing in the show. In the television industry in Taiwan, most TV channels do not establish a reserved price for each show and the price is in general negotiable. To guarantee the profit of the TV channel, we suggest setting a reserved price (R_s) for each show s as it was used in the model of Jones and Koehler (2002). Such a requirement is operated at an aggregate level and is based on the after-adjustment bid prices, i.e.,

$$\sum_b p'_b y_b \geq \sum_b \sum_s x_{b,s} R_s \tag{3}$$

Each show has its maximum number of commercial time units, K_s and thus the following equation maintains the feasibility of the total number of units that can be placed in a show:

$$\sum_b x_{b,s} \leq K_s, \forall s \tag{4}$$

Time units can be allocated to a bidder only when he has a winning bid, i.e., $y_b = 1$. Equation (5) enforces the relation between the unit allocation decision $x_{b,s}$ and y_b:

$$\sum_s x_{b,s} \leq \left(\sum_s K_s \right) y_b, \forall b \tag{5}$$

Limiting the time units of a commercial appearing in each show allows the buyer to spread his commercials over the campaign period. An upper bound is set by the bidder to express such a preference as shown in Eq. (6). At the same time, the bidder can also set a lower bound, i.e., $L_{b,s}$ in Eq. (7), to specify the minimum number of time units he requires in a show if the show is allocated to him, i.e., $j_{b,s} = 1$:

$$x_{b,s} \leq U_{b,s}, \forall b, s \tag{6}$$

$$x_{b,s} \geq L_{b,s} j_{b,s}, \forall b, s \tag{7}$$

Equation (7) also enables a bidder to do spot buy when $L_{b,s}$ is greater than 0. The relation between $x_{b,s}$ and $j_{b,s}$ can be enforced through the following equation:

$$x_{b,s} \leq K_S j_{b,s}, \forall b, s \tag{8}$$

The CPRP buy is achieved by the following constraint:

$$\sum_s x_{b,s} E_s \geq T_b y_b, \forall b \tag{9}$$

where, E_s is the vector of estimate viewing rates of individual audience groups of the show and it is defined as:

$$E_s = \begin{bmatrix} e_{s,1} \\ \vdots \\ e_{s,g} \end{bmatrix} \tag{10}$$

where, $e_{s,g}$ is the estimated viewing rate of the g-th audience group of the show. The target GRP vector T_b demanded by the bidder is defined as:

$$T_b = \begin{bmatrix} t_1 \\ \vdots \\ t_g \end{bmatrix} \tag{11}$$

where, t_g is the target GRP of the g-th audience group.

It is noted that, though Eq. (7) allows the bidder to specify the shows he demands, the TV channel may not necessarily assign the show to the bidder. In our model, the bidder can protect his benefit by specifying the minimum number of allocated shows he desires. Such a preference of the bidder is accommodated by the following equation:

$$\sum_s h_{b,s} j_{b,s} \geq H_b y_b, \forall b \tag{12}$$

where, $h_{b,s}$ indicates if show s is demanded by bidder b, $h_{b,s} = 1$ indicating yes, 0 otherwise.

The integrity of our decision variables is maintained by:

$x_{b,s}$, $k_{b,s}$ are integers and $x_{b,s}$, $k_{b,s} \geq 0$, $\forall b, s$, $y_b \in \{0,1\}, \forall b$ and $j_{b,s} \in \{0, 1\} \forall b, s$.

The nomenclature used in the above model is summarized below:

Decision variables:

y_b : 1if bidder b is selected, 0 otherwise
$x_{b,s}$: Number of units in show s assigned to bidder b
$k_{b,s}$: Number of times that bidder b's commercial is played in show s
$j_{b,s}$: 1 if a commercial of bidder b is assigned in show s ($x_{b,s}$>0), 0 otherwise

Parameters:

$l_{b,s}$: Length of the commercial demanded by bidder b in show s, measured in unit, 1 unit = 10 sec
p_b : Bid price submitted by bidder b
p_b' : p_b adjusted by the auctioneer
c_s : Credit (or debt) endowed to show s, if show s is a non-primetime show, c_s is a credit ($c_s \geq 0$, virtual money given to bidders); otherwise it is a debt (c_s<0)
R_s : Reserved price for show s
K_s : Available inventory (units) in show s
M : A very large number
$U_{b,s}$: Maximum units allowed in a show, requested by bidder b
$L_{b,s}$: Minimum units required in a show, requested by bidder b
E_s: Estimates of rating points of show s
T_b: GRP demanded by bidder b
$h_{b,s}$: Assigned by bidder b, 1 if show s is demanded, 0 otherwise
H_b: Minimum number of shows assigned to bidder b that match the bidder's demand

NUMERICAL EXAMPLE

To illustrate and evaluate the performance of the proposed combinational auction model for the TV advertising market in Taiwan, we take the one-month show schedule of a TV channel in Taiwan and simulate a combinatorial auction for this TV channel. Many of the parameters in our model are classified information of the TV channel and cannot be obtained or revealed. Alternatively, the values of such parameters are randomly generated within reasonable intervals of these parameters. The generated data had been examined by an executive of the TV channel and their validity was confirmed.

There are around 30 major media agencies in Taiwan, so the number of bidders in our example is set to be 30 accordingly. In Taiwan TV advertising market, 70% of the purchases are CPRP buys, while 30% are spot buys; thus the types of bids are randomly generated roughly according to this ratio. Bid prices are also randomly generated according to the time slots demanded in the bid and the list prices published by the TV channel. The generated bid prices were validated by the executive of the TV channel.

In our model, the use of virtual money to encourage purchase of time slots in unpopular time tiers is a new concept in TV commercial trading. Thus, there is no reference for the setting of this parameter. To justify the effect of virtual money on the time slot allocation result, we determine from the computational results a suitable range for the different amounts of virtual money. The formulation of the optimization problem for the above example yields 60510 variables (containing 20190 binary variables) and 81554 constraints. The problem is solved by LINGO 12.0 running on a PC with an Intel® Core(TM)2 Duo CPU E8400 @ 3.00 GHz and 1.96 GB RAM.

There are two main experiments: a feasibility evaluation of the proposed combinatorial auction and an evaluation of the effect of virtual money on the auction results. In the first experiment, time tiers of the TV channel are divided as those listed in Table 1 and the amount of virtual money associated with Tiers A, B and C is NT$0, NT$700 and NT$1400, respectively. The total numbers of units for Tiers A, B and C in a month are 9800, 15400 and 8400, respectively. Ten replications are run for this experiment and the results are shown in Table 3.

Table 3: Combinatorial auction results of the example

			Number of winning bids			Unsold units		
Replication #	CPU time (s)	Revenue (NT$)	Spot buy	CPRP buy	Total	A	B	C
1	135	191,033,700	6	19	25	0	325	361
2	140	191,543,600	6	19	25	0	337	343
3	137	198,845,200	6	19	25	0	356	339
4	145	189,874,300	6	18	24	0	310	307
5	150	200,056,400	7	18	25	0	375	398
6	133	197,544,600	6	19	25	0	343	337
7	138	197,677,500	6	19	25	0	339	358
8	142	187,433,200	6	19	25	0	342	356
9	151	189,644,300	6	19	25	0	336	364
10	132	200,642,200	6	19	25	0	351	362
Average	140	193,429,500	6	19	25	0	341	353

Table 4: Average numbers of units obtained and costs

	Tier A	Tier B	Tier C	Average cost per unit (NT$)
Spot buy	672	597	77	27537
CPRP buy	303	678	326	5631

The auction results of the ten replications are consistent. The average revenue is NT$193,429,500 with a deviation of NT$4,716,646. The average unsold units of Tier C is 353, which is 5% of the total number of units in this tier; Tier B has on average 341 unsold units, which is 2% of its total number of units, while all units of Tier A are sold out. The executive of the TV channel had reviewed the above results and considered the solutions satisfactory. The average number of units obtained by the winning bidders and their average costs per time unit are shown in Table 4. As expected, the unit cost of CPRP buy is much lower than that of spot buy.

To evaluate the effect of virtual money on the auction result, we set four scenarios with different amounts of virtual money for each tier. In Scenario 1, there is no virtual money for all tiers. In Scenario 2, the amount of virtual money associated with Tiers A, B and C is NT$0, NT$700 and NT$1400, respectively; and the same amount for each tier is doubled in Scenario 3 and tripled in Scenario 4. Bidders specify the time slots they demand only in spot buy; thus to eliminate the effect of CPRP buy on the auction result, all the bids in this experiment are formed as spot buys only. Ten replications are conducted for the auction and the results are shown in Table 5.

In each replication, the problem is solved for the four scenarios. After conducting an ANOVA on the revenues resulting from different amounts of virtual money given, no significant difference among the four scenarios is found, as shown in Table 6. On the other hand, an ANOVA on the unsold units of Tier C for different amounts of virtual money given indicates significant differences among the four scenarios (F = 33.13 and p-value = 0.00). Pair-wise t-tests are further conducted and the results are presented in Table 7. As can be seen, the numbers of unsold units in Scenarios 1, 2 and 3 are similar while that in Scenario 4 is significantly different. This result implies that to alter the time slot allocation decision, the amount of virtual money should be set as that in Scenario 4. The amount of virtual money given to Tier C in Scenario 4 (i.e., 4200) is about 35% of the reserved price of time slots of Tier A.

CONCLUSION

In this study we have presented a combinatorial auction mechanism for the TV advertising market in Taiwan. The proposed combinatorial auction mechanism enables the advertisers to bid for a set of time slots simultaneously, thus avoiding the problem of losing any item in the bidder desired bundle. Two types of TV advertising procurement are considered in our study, namely spot buy and CPRP buy. Spot buy allows a bidder to specify certain time slots he demands; while CPRP lets a bidder demand the target viewing rates for various viewing groups and the TV channel will determine the time slots to reach the bidder targets. Furthermore, to encourage advertisers to purchase the time slots in unpopular time tiers, we suggest using virtual money endowed to bids that contain such time slots to raise their chances of winning the bidding.

This study models the TV commercial combinatorial auction as an integer programming problem and uses one-month time slots of a TV channel in Taiwan as a case study. The problem is solved by LINGO 12.0 and the solutions demonstrate the feasibility of applying our approach to a real-world problem. To evaluate the effect of virtual money on the auction result, we set four scenarios with different amounts of virtual money in the model. Computational results suggest that the amount of virtual money set must be at least 35% of the reserved price of time slots in primetime shows in order to

Table 5: Auction results of different amounts of virtual money

	Amount of virtual money (A/B/C)															
	Scenario 1 (0/0/0)				Scenario 2 (0/700/1400)				Scenario 3 (0/1400/2800)				Scenario 4 (0/2100/4200)			
		Unsold units				Unsold units				Unsold units				Unsold units		
No.	R.*	A	B	C	R.	A	B	C	R.	A	B	C	R.	A	B	C
1	198	52	1850	5179	199	55	1862	5217	188	48	1920	5087	198	78	1960	5078
2	188	55	1792	5220	191	53	1887	5048	191	46	1824	5197	201	81	2011	4792
3	194	63	1776	5162	191	48	1898	5177	196	51	1854	5235	189	75	1879	4977
4	188	48	1843	5314	190	61	1892	5248	196	51	1854	5235	189	75	1879	4977
5	194	47	1842	5178	200	60	1670	5320	198	61	1931	5162	188	79	1988	5216
6	198	57	1950	5512	197	51	1992	5407	201	60	1954	5209	195	71	2023	5329
7	186	40	1863	5177	198	43	1983	5210	198	52	1867	5307	197	92	2125	4771
8	174	32	1922	5230	187	38	1785	5177	188	41	1792	5548	192	87	1978	4895
9	189	62	2007	5348	190	47	1846	5200	200	40	2013	5492	201	69	2037	4539
10	190	51	1889	5271	201	44	1976	5161	186	56	1854	5179	185	86	2164	4683
Avg	190	51	1873	5259	194	50	1879	5216	194	51	1886	5265	193	79	2004	4926

*: R. is the revenue in NT$1,000,000

Table 6: Analysis of variance on revenues in different scenarios

Source of variation	SS	Degree of freedom	MS	F	p-value
Scenarios	132.6	3	44.20	1.29	0.29
Error	1235.4	36	34.32		
Total	1368	39			

Table 7: Pair-wise t-tests on unsold units of tier C between different scenarios

	Scenario 2	Scenario 3	Scenario 4
Scenario 1	t = 0.22, p = 0.83	t = 0.03, p = 0.99	t = -5.70, p = 0.00
Scenario 2		t = -0.24, p = 0.82	t = -7.26, p = 0.00
Scenario 3			t = -8.87, p = 0.00

encourage advertisers to purchase time slots in less popular time tiers.

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