Study of Whether Online Review Platforms Convey Valid Quality Information

-- Evidence from Escape Rooms in Beijing

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Abstract. The escape room, as an emerging popular live-action entertainment project in recent years, has become more and more popular among the young generation. Online review platforms have become one of the important channels to disseminate quality information to consumers in this emerging industry. However, critics doubt the credibility of the online platform as a reliable information channel and its influence on consumer choices of escape rooms. Do online review platforms convey valid quality information to the public? Are the prices of coupons an illusion? We seek to answer these questions by investigating the MeiTuan platform, one of the leading online review platforms in China. We apply the method of NLP technics to extract high-frequency words from customer reviews and use linear regression to measure the effect of prices on discount rates. We observe that there was no significant correlation between the store's ratings and the type and the number of coupons the store offered. However, customers with different ratings have different claims in their reviews. Moreover, a price increase has a negligible impact on the discount rate, implying that the platform almost uses a unified discount pricing strategy.

Keywords: Escape Room; Willingness to Consume; User Satisfaction; Online Reviews; Pricing Strategy.

1. Introduction

In recent years, the escape room industry has grown rapidly and has become one of the preferred entertainments for young people. The iiMedia Research finds that the escape room ranked fourth in the list of China's post-95 favorite emerging entertainment, and the year-over-year growth rate of order volume reached 98.1%.(See https://www.163.com/dy/article/H96MEDDP0511A1Q1.html) According to the statistics of the 2020 China Escape Room Industry Development Status and User Behavior Insight Analysis Report, the number of escape room stores in China reached 15,152 in 2019, an increase of 4,469 over 2018; The number of escape room brands reached 10,673, an increase of 1,010 over 2018; The market size of the escape room industry is nearly 10 billion yuan, and the number of consumers has reached 2.8 million.(See https://new.qq.com/rain/a/20211118A025XP00) Escape rooms have been constantly updated and iterated, and the strong sense of immersive experience has also attracted more and more new consumers, and the market size is expected to reach 17.59 billion yuan in 2026.(See https://www.163.com/dy/article/H96MEDDP0511A1Q1.html) Online review platforms have emerged as one of the most popular information channels to disseminate quality information to consumers in leisure and entertainment projects. Among them, MeiTuan, founded in 2010, is one of the most well-known online life service e-commerce platforms in China. Its business covers 2,800 counties and cities in China and aims to help consumers to eat better and live better. In 2019, its annual revenue increased by 49.5% year-on-year to 97.5 billion yuan, the total transaction amount of the whole year increased by 32.3% year-on-year to 682.1 billion yuan, and the annual trading users of the platform reached 450 million. (See https://baijiahao.baidu.com/s?id=1662592590891276348&wfr=spider&for=pc) According to the 2020 Q3 financial report, the annual trading users are 480 million, the average number of transactions per user is 26.8 per year, and the number of active stores is 6.5 million. (See https://tech.ifeng.com/c/81p8MkcgHyO) On MeiTuan platform, consumers can rate stores and services on a scale of zero (lowest) to five (highest), and upload photos to share their experiences of using coupons. From consumers' perspective, MeiTuan allows consumers to choose from a variety of goods and services. From stores' perspective, MeiTuan collaborate with them to increase their exposure, build their online reputation, and thus improve their consumer flow.

Despite its popularity, critics question the credibility of MeiTuan as a reliable information channel and its influence on consumer choice. First, the quality of products sold by some stores on this platform is difficult to guarantee. For example, the 21st Century Business Herald reported that medical products offered by some stores had not been registered with the National Food and Drug Administration. (See https://pcedu.pconline.com.cn/1360/13609805.html) Second, MeiTuan once allowed users to review on the platform without purchase. (See http://news.sina.com.cn/s/2020-09-02/doc-iivhuipp2103454.shtml) As a result, there might be a lot of false and misleading reviews on the platform. Third, interestingly, almost all stores apply discounted pricing strategies. It remains unclear to the public whether the original prices are simply an illusion. MeiTuan has also had many other highly controversial incidents including unfair competition (See https://finance. sina.com.cn/tech/2021-04-14/doc-ikmyaawa9626481.shtml) and leakage of user information. (See https:// baike.baidu.com/item/%E7%BE%8E%E5%9B%A2/5443665#7_6) Due to these concerns and reports, the public has developed some mistrust of the information provided by MeiTuan.

The goal of our research is multifaceted. Firstly, we would like to understand, in the context of the escape room industry, whether MeiTuan, as a proxy of social media, conveys accurate quality information to the public. Secondly, what features of the escape room do customers care about? Finally, we explore the stores' pricing strategies for coupons on the platform. Such an exploration would enable us to identify whether the price is "truly" discounted.

2. Data Sources and Sample Construction

We collect data from MeiTuan, a well-known online review platform providing escape room information to consumers. We choose the escape room in Beijing and collect the information including store links, store names, store ratings, store location, coupon names, coupon prices, customer reviews, etc. We collect 251 stores listed on MeiTuan associated with 1,750 coupons and 41,825 consumer reviews that were published from July 28, 2013, to April 20, 2022. We delete the stores without any reviews (13 stores) or without any coupons that sell (32 stores). We also delete duplicate coupons in the same store and a variety of non-meaningful reviews such as the same reviews from the same customer; only ratings but no reviews. Our final sample consists of 206 stores with 973 valid coupons (55.6%) and 14,396 reviews (34.4%).

3. Analysis

In this section, we present our main analysis of MeiTuan. In Section 3.1, we focus on the basic characteristics of coupons offered by the stores in Beijing. In Section 3.2, we utilize NLP techniques to extract valuable information from customer reviews. In Section 3.3, we analyze stores' pricing strategy of coupons on MeiTuan.

3.1 Characteristics of Coupons

In this section, we provide some basic information about escape rooms in Beijing, including the number of stores, the number of store coupons, the number of store reviews, etc. Our dataset involves 973 coupons, collected from 206 different stores listed in MeiTuan. On average, each store offers 5 coupons.

We now analyze the features of coupons. We divide these coupons into 6 classes by detecting the keywords contained in their names, namely, room-specific coupons, team building, board games, refill cards, tips, and food and beverages. The definition for each class and its associated keywords is displayed in Table 1. Team building class refers to events that are customized by multiple people including birthdays, marriage proposals, and company parties (e.g., the coupon of *Meta Universe*

Science and Technology with at most 35 people). Board game refers to board games (e.g., the coupon of *Bloody Clock Tower*). Refill cards allow customers to recharge with a discount (e.g., the coupon of *enterprise stored value card*). Tips class and food and beverages class, respectively, refer to tips for staff (e.g., the coupon of *NPC reward coupons*) and coupons for food and drinks (e.g., the coupon for *unlimited snacks*). It is worth mentioning that the name of room-specific coupons usually contains the name of a specific escape room (e.g., the coupon of *Agent Union*), and thus we check these coupons manually. Figure 1(a) suggests that the class of room-specific coupons accounts for the majority (75.5%), and that of the food and beverages class accounts for the minority (0.51%). Customers rate stores based on the in-store experience of the coupons they choose. The full score of these stores is 5.0, and the distribution of the scores ranges from 3.0 to 5.0. Figure 1(b) shows the specific distribution of store ratings. 187 (about 90%) stores were given a rating above 4.0; 73 (about 35%) stores were given a perfect score of 5.0.

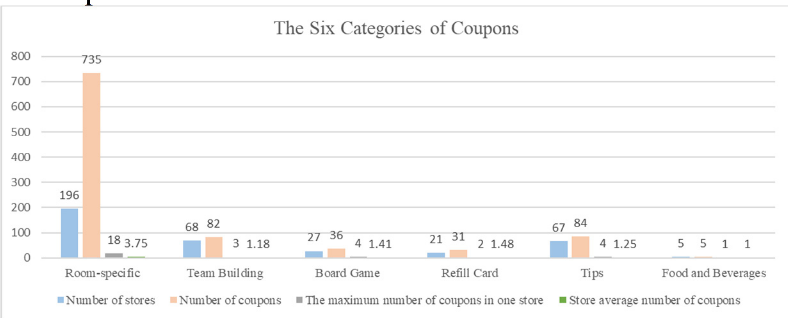


Figure 1(a). The Distribution of The Six Catsgories of Coupons

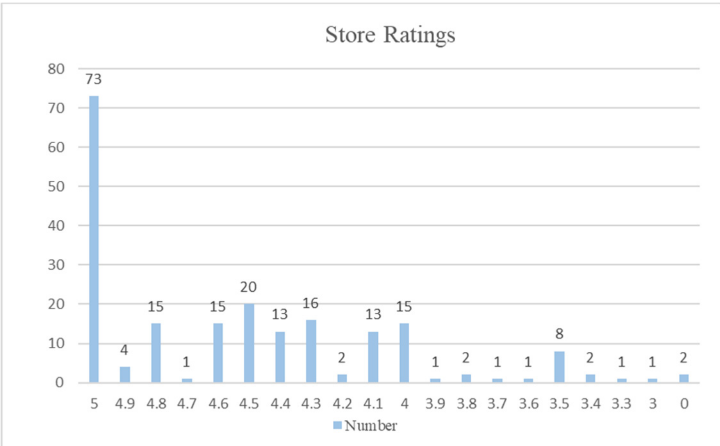


Figure 1(b). The Distribution of Store Ratings

Table 1. The Keywords for Each Class

Classification	Team Building	Board Game	Refill Card	Tips	Food and Beverages
The keywords	party	board game	value card	NPC	wine
	customization	murder mystery game	membership card	tip	beverages
	birthday	werewolf kill	vouchers	small flowers	cakes
	marriage proposal	warm-up game	coupons	chicken legs	snacks

3.2 User Reviews

On MeiTuan, customers can freely review and rate a store to express their feelings about this escape room. To make the results more reflective of the actual situation based on different customer feelings, and to avoid a large number of high-scoring reviews obscuring a small number of critical reviews, we first divided the reviews into five *review sets*. Specifically, reviews with ratings, 5 and 4.5, 4 and 3.5, 3 and 2.5, 2 and 1.5, and 1 and 0.5, are regarded as one set, respectively. Figure 2(a) shows the distribution of the five review sets. We observe that reviews with extremely high ratings account for a large proportion of all reviews (74.1%), while reviews with extremely low ratings account for 3.1%.

For each set of reviews, we apply the NLP techniques to extract qualitative characteristics (i.e., the frequently mentioned topics) from the consumer reviews' content. To be more explicit, we use JiebaR, a Chinese word segmentation tool, to tokenize the sentences and delete meaningless stopwords. We then calculate the respective perplexity-consistency curve and choose the optimal number of topics with the smaller implied perplexity and higher implied consistency. Based on the initial selection of the optimal number of topics, we used the LDA toolkit to extract topics from the reviews in the five review sets and used the LDAvis toolkit to visualize the results of the topic division. We obtained the top 30 high-frequency words of each topic for each review set. According to these high-frequency words, we find those words without practical meaning and consider them as additional stopwords. We loop through the above operations so that all the high-frequency words have practical meaning.

Figure 2(b) shows the resulting distribution of the perplexity-consistency curves of the five review sets from the lowest to the highest ratings. We can find that as the number of topics increases, the degree of perplexity continues to decline, and the consistency curve is not necessarily decreasing. Together with a manual check of high-frequency words, we determine that the optimal numbers of topics for each review set are 8, 6, 6, 6, and 9.

Combining the original meaning of these high-frequency words with the actual meaning of their appearance in the text, we manually categorized multiple topics and added the proportion of each review in each of the five review sets to each topic respectively. The proportion of the reviews of the five review sets in multiple topics determined by the LDA model and manual review is calculated respectively. Figure 2(c) shows the distribution of review topics for five review sets. Among them, in the review sets with ratings of 5 and 4.5, 4 and 3.5, and 3 and 2.5, we manually classify the topics into five categories, namely, plot, environment, service, comprehensive evaluation, and difficulty. In the two review sets with ratings of 2 and 1.5, and 1 and 0.5, there are four categories of topics, namely, plot, environment, service, and comprehensive evaluation. Table 2 summarizes the high-frequency words for each topic. We observe that high-frequency words are different in different review sets.

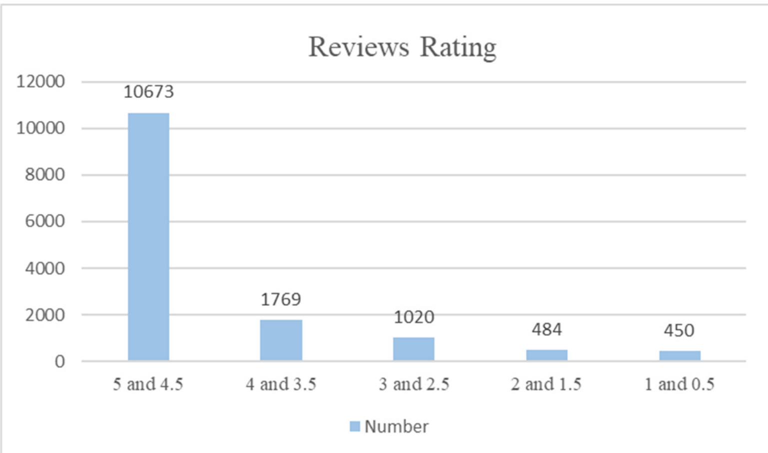
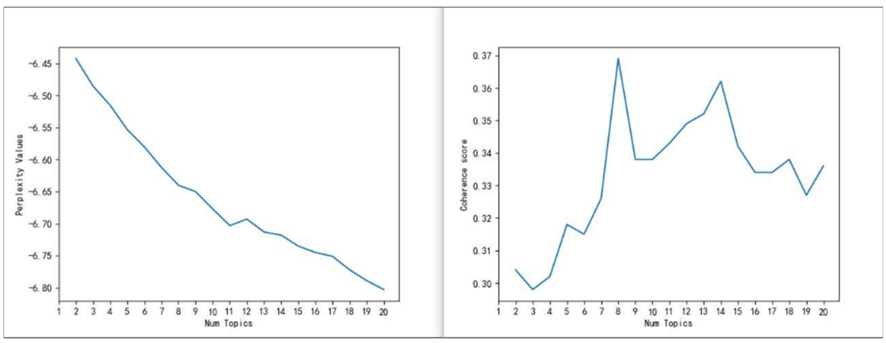
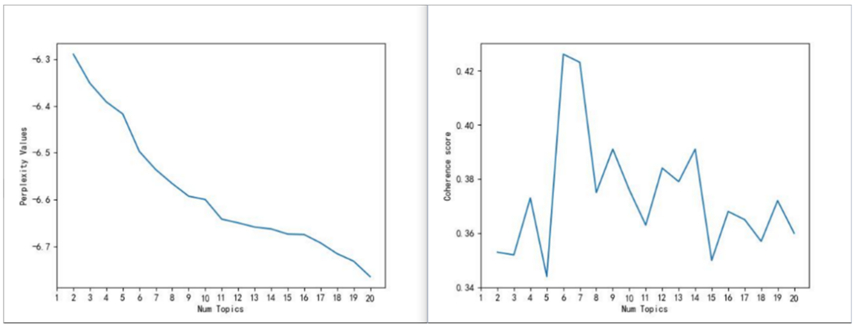


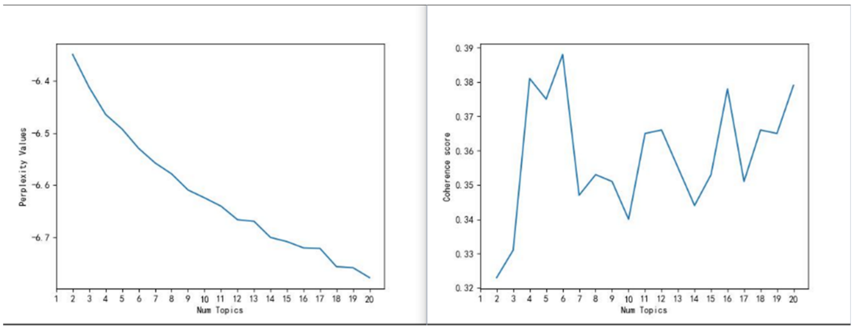
Figure 2(a). The Rating Distribution of The Five Review Sets



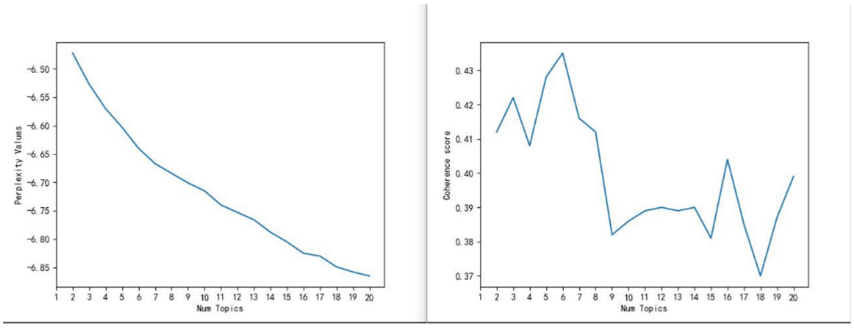
1 and 0.5:



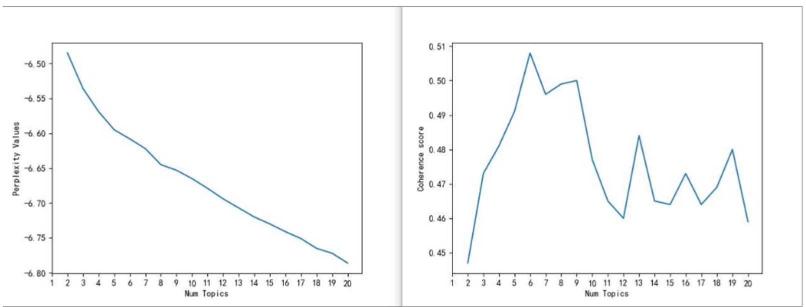
2 and 1.5:



3 and 2.5:



4 and 3.5:



5 and 4.5:

Figure 2(b). The Perplexity-Consistency Curves of The Five Review Sets

We found that in reviews that were extremely dissatisfied with the escape room project (i.e., reviews with ratings 2 and 1.5, 1 and 0.5), customers rarely mentioned questions about the difficulty of the room itself. This also resulted in only four topics in the reviews of these two text bases. For these escape room projects, they prefer to talk about the service of the escape room (more than 42% of reviews in rating of 1 and 0.5) and the plot (in rating of 2 and 1.5 out of 33% of reviews), and we guess poor service or plot can lead to a sharp drop in ratings. Conversely, in reviews that gave the escape room project a medium or higher rating (i.e., reviews with ratings 3 and 2.5, 4 and 3.5, 5 and 4.5), relatively more customers would prefer a further comprehensive evaluation of the entire room (with the increase of the score, the proportion gradually increased from 28.9% to 38.1%), after mentioning topics such as plot, environment, service. This implies that when the customers are satisfied with all aspects of the room, they will not be too obsessed with evaluating a particular aspect of the room. They will use the words like "nice" and " want to come again" to make an overall inductive evaluation. We further observe that in the reviews with ratings 3 and 2.5, 4 and 3.5, and 5 and 4.5, topics of plot, environment, and service are relatively flat (about 18%), and the topic of difficulty drops from 17.6% to 8.8%.

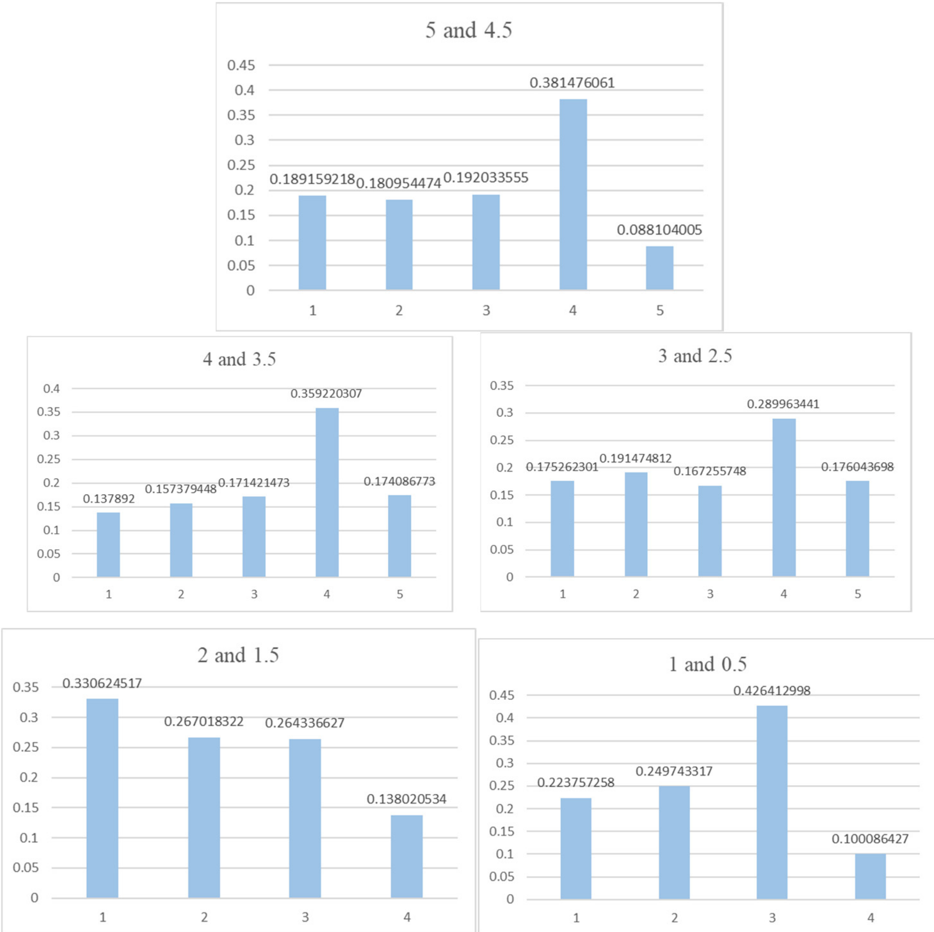


Figure 2(c). The Distribution of Review Topics for Five Review Sets

Table 2. The High-Frequency Words for Each Topic

The plot	The environment		The service	The comprehensive evaluation	Difficulty
clues	the external environment	easy to find	the little sister	praise	brain burning
design		subway	staff	worthy	help
cleverness		location	front desk	perfect	simple
experience		traffic	NPC	also come	prompt
logic		new opening	customer service	happy	IQ
deduction		elevator	attitude	interesting	pass
ending		air conditioning	reception	fun	timeout
details			explanation	recommend	moderate
boredom	the interior environment	space	puzzle	like	novice
plot		decoration	appointment	good	success
articulation		lighting	dedication	general	smooth
interstellar		atmosphere	responsibility	overall	puzzles
crossing		equipment	interaction	not fun	easy
Three Kingdoms		scenes	enthusiasm	nothing	difficult
assassination		reduction	gentleness	not worth it	hint
side lines		immersion	good looking	value for money	appropriate
themes		mechanical	impatient	bored	stupid
horror		sound effects	patience	bad	defeat

3.3 Coupon Pricing and Discounts

On MeiTuan, stores offer coupons to consumers. In the coupon dataset, we also keep the pre- and post-discount prices for each coupon. Figure 3 shows the distribution of coupon prices and discounts in the six categories. The prices vary, and the pre-discount price (i.e., in-store price) depends on the store location (in the suburbs or urban areas), the store ratings, the type of coupon, etc. In this section, we study the factors that affect the coupons' pricing strategies. Our model is specified as follows:

$$discount_{ij} = \alpha_0 + \alpha_1 price_{ij} + \sum_{s\in S} \alpha_s\, coupon\_s_{ij} + \theta_j + \epsilon_{ij}.$$

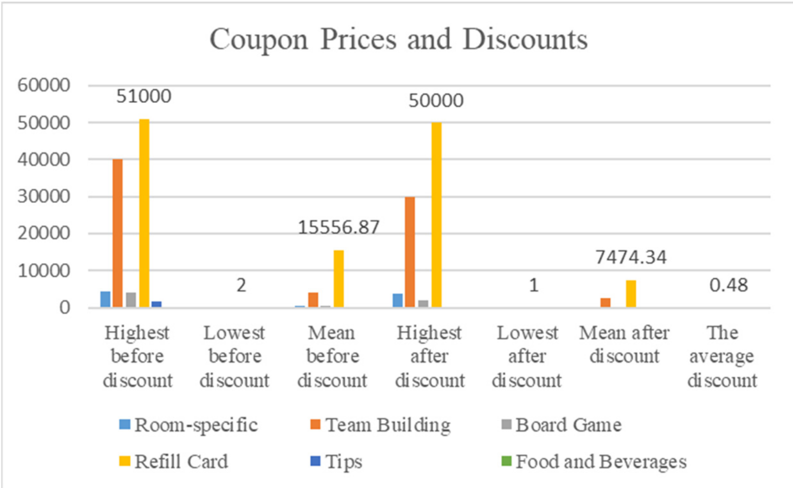


Figure 3. The Distribution of Coupon Prices and Discounts in The Six Categories

Table 3. The Impact on The Discount Rate

<table>
<tr><td></td><td colspan="2">Dependent variable:</td><td></td><td></td></tr>
<tr><td></td><td>paste0(reg1, "| store_</td><td>paste0(reg2, "| store_name| 0| 0")</td><td></td><td></td></tr>
<tr><td></td><td>(1)</td><td>(2)</td><td></td><td></td></tr>
<tr><td>coupon_price</td><td>-0.0002**</td><td>-0.0002***</td><td></td><td></td></tr>
<tr><td></td><td>(0.0001)</td><td>(0.0001)</td><td></td><td></td></tr>
<tr><td>type_Room-specific</td><td></td><td>0.002</td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.048)</td><td></td><td></td></tr>
<tr><td>type_Team Building</td><td></td><td>-0.285***</td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.053)</td><td></td><td></td></tr>
<tr><td>type_Board Game</td><td></td><td>-0.118*</td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.064)</td><td></td><td></td></tr>
<tr><td>type_Refill Card</td><td></td><td></td><td></td><td></td></tr>
<tr><td>type_Tips</td><td></td><td>-0.383***</td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.054)</td><td></td><td></td></tr>
<tr><td>type_Food and Beverages</td><td></td><td>-0.241**</td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.116)</td><td></td><td></td></tr>
<tr><td>Observations</td><td>973</td><td>973</td><td></td><td></td></tr>
<tr><td>Adjusted R2</td><td>0.159</td><td>0.372</td><td></td><td></td></tr>
<tr><td>Note:</td><td>*p<0.1;</td><td>**p<0.05;</td><td>***p<0.01</td><td></td></tr>
</table>

The dependent variable $discount_{ij}$ represents the discount rate of coupon i of store j. The explanatory variable represents $price_{ij}$ the price of coupon i of store j (Yuan in hundreds). There is a set of control variables in the model. Specifically, $coupon\_s_{ij}$ is a binary variable, if the coupon i is classified to the coupon category $s \in S$, then the variable is equal to 1, where S = {room-specific coupon, team building, board game, refill card, tips, food, and beverages}, and equals 0 otherwise. For example, $type\_room - specific_{ij}$ represents whether the coupon i of shop j belongs to the room-specific coupon class. In addition, we include store j's fixed effect θ_j to control for its time-invariant factors including store ratings, the number of reviews, the number of stores coupons, etc. ϵ_{ij} is an error term. We cluster standard errors by stores.

We now examine the impact of price on the discount rate, as shown in Table 3. Column 1 shows the basic results. The coefficient of price is 0.002, indicating that a two thousand yuan increase in price only leads to a negligible decrease in discount, though significant. This implies that the price does not affect the discount rate. In column 2, we use the class of refill card as a benchmark to show the results when involving more control variables, and the results are consistent with those shown in Column 1. We deduce that the platform uses a "uniform" discount pricing strategy on coupon pricing.

4. Conclusion

The goal of this study is to explore whether online review platforms convey valid quality information to consumers in the context of the escape room industry. To achieve this goal, we study the information on store and coupons, consumer reviews, and pricing policy on the MeiTuan platform, one of the most well-known online life service e-commerce platforms in China.

One of our key findings is that the presentation of MeiTuan seems unclear to consumers, particularly, because there is no obvious reference for how a store's rating is obtained, and the customer does not get some valid information about the store's coupons from the store's rating. Moreover, the platform uses a "uniform" discount pricing strategy on coupon pricing, say, the original price does not have an impact on the discount rate.

Due to some recent years' reports on MeiTuan, the public has generated mistrust of the online platform. Therefore, the platform must take action to restore the public's perception of the information disclosed. We believe that it might be helpful for the platform to collaborate with the government to standardize its rating system.

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