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Purchase Uncertainty: The Opportunity for Culture Creative E-Commerce during Covid-19

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Abstract: This research focuses on a successful culture creative company, which is famous for its blind-box product, and discusses its sales tactics based on demand uncertainty. Sales related data were adopted, covering also the pendemic period in 2020. This study ran t-test for variables and regression analysis based on OLS. After regressing sales volume and customer flow on sales income in the first stage, this research continues to use the residuals as dependent variable in the second stage, which reflected the uncertainty of customer behavior that beyond prediction. Concluding existing literatures, the number of items per transaction (“ldl”) is used to be the primary independent variable in the second stage, with new product launch as control variable. This research finds that “ldl” and its squared item influence purchase uncertainty significantly, especially for epidemic period. Therefore, this research has practical meanings to those culture creative e-commerce firms to seize the opportunities for recovery after epidemic time, as well as theoretical contribution by introducing two-step OLS regression into the study on ecommerce.

1. Introduction

Since the concept of culture creative was firstly pointed out by UK in 1980s, it has attracted the attention from the entire world. Culture creative industry had contributed greatly to economy for most countries by offering multiples choices for spiritual enjoyment. With the wide spread of animation, anime’s derivative products have become more and more popular. As special kinds of derivatives, capsule toys earned great popularity, initiated from Japan based on comic and anime. Similarly, another Japanese typical culture raised another wave, which is called Fukubukuro. It is the package sold on New Year’s Day at fixed price containing unknown products. It is also known as blessing-bag. Both these two merchandises have similar feature, which is the lottery way of purchase. Such feature indeed attracts customers’ attention nowadays, especially for products of low necessities, such as culture creative products.

Hence, so-called blind-box, same packing with cartoon minifigures inside, gained great popularitties. Attractive products that can only be obtained by luck make customers feel enjoyable during the purchasing process. Since the exact model of product remains unknown until the box is opened, customers may expend extra money until being satisfied. Furthermore, since the market value of each model varies, some gamblers are hoping to buy the most expensive one at a comparatively low price, because all blind-boxes are charged with an average price. Opportunists are also active for resale in order to get profit. Such marketing tactics make all kinds of capsule toys successful during the past years. On one hand, demands represented by sales volumes are amplified because of the lottery business model. On the other hand, customers' phycological experience accelerated the flourishing process of such culture creative market.

Unlike agriculture, culture creative consumption is unnecessarily rigid for human survival, which means it may be influenced to a large extent by macro environment. These force-majeures for civil life include economic depression or nature disaster. In the beginning of the year 2020, coronavirus brought tragedies to the whole world. Civilians will definitely suffer from the economic consequences during or even after the epidemic period. Eventually, all industries will recover from downturn. Among all industries, culture creative seems to be one the most special industries due to its spiritual and entertaining characteristics. But on the other hand, people's daily life nowadays is guaranteed with enough supplements, which means even during epidemic period it is still possible for some culture creative products to remain with good market performance, especially online service such as live. But offline scenarios encounter severe situation. The sales of products represented by capsule toys and blind-boxes are dependent on the volume of customer visits to the stores. On the other side, when people have more leisure time at home, their attentions towards specific products may increase. So, companies are facing a dilemma: higher potential demands but lower volume of visits. "How can these culture creative firms operate their e-commerce businesses in order to maximize total revenue" seems to be an interesting research question.

In digital age, culture creative products can be either "online only", "offline only" or "combination of on- and off-line". Online products or services are less likely to be involved by physical environment. But off-line businesses' performances are facing tragedy when the epidemic in 2020 falls. For those businesses that combining online and offline elements, their business performances in epidemic time and how they can maximize their revenue seems to the questions worth studying. Moreover, when epidemic period is finally over, market consumptions may rebound dramatically. Seizing this opportunity will be significant for all companies.

Consequently, this research will make use of the business performance data of the stores of outstanding culture creative companies that running online and offline marketing as well as offline stores, and then try to discuss the influences from the volume of customer flows and consuming characteristics based on quantitative analysis.

2. Theory Foundations

2.1. Key independent variable: number of items per purchase

Culture has been always evolving in the history. The process of globalization and development of Internet accelerated the spread of culture and art. Fukubukuro was firstly appeared in Japan. The exact contents in the bag of New Year sales remain unknown to the consumer before purchase[1]. And now similar product or business model had appeared elsewhere in the world, especially China. They found that potential gains to a monopoly seller for marketing goods in lottery way rather than separately are only positive for lotteries where there is a higher probability of obtaining higher valued good. On the contrary, if higher valued or more favorable goods can be obtained with the highest probability, customer experiences will be different. That is to say, customers want to be surprised but not disappointed[2]. The store must make a tactical balance in setting the probabilities for products or leasing information about promotion, or expanding product portfolio to attract them.

Consequently, it is necessary to analyze how customers behave when making consumption decisions. Consumers with more parent-brand experience will be more likely to try the extensions, however, they may be less likely to repurchase the extension because of the selection bias[3]. Hence, for the lottery-like product such as blind-box, magnifing demands by introducing lottery mechanism seems to be an effective tactic to stimulate consumptions. Therefore, setting a proper main-to-ancillary ratio may be necessary, but it can only be settled after customers consumption habits are known well. Considering customers' shopping behaviors may vary from each other, this research tends to adopt the number of items per purchase as a dependent indicator for the study on business performance.

Another issue for discussion is the online or offline scenario for this study. Customers with greater product involvement tend to shop in offline shopping malls, where they could obtain more information on products[4]. For blind-box, the situation is quite similar, for the reason that demographic and most psychological factors, as well as web-savvy features of a virtual storefront appear non influential in determining the probability of an Internet user making a purchase[5]. If a customer fancy a blind-box product, the shopping process is also enjoyable for him/her[6]. Therefore, this research will collect the data from offline stores only, though the marketing activities such as announcement for new products' launch are online and coordinated by the headquarter only. By doing so, endogeneity bias caused by sampling can also be avoided.

2.2. Dependent variable: Uncertainty of purchase

Sales income of a company has been studies as dependent variable in countless studies. Comparing with the total volume of sales that could be obtained for certain, how sales fluctuate beyond prediction or expectation might have better significance to the company[7]. Kim and Sullivan emphasized the concept of "uncertainty" for such discussions[3]. Research on online purchase behavior also took uncertainty into consideration[8]. And one cause of uncertainty is curiosity, retailers can use mystery to drive purchase motivation[9], which means even with the same product, sales can be increased by stimulating customers' phycological curiosities. It is believable that such mechanism still works for blind-box. Uncertainty in sales income will be used as dependent variable in this research, for the reason that the product itself is full of uncertainty, which make customer purchase fluctuate within a wider amplitude.

Perspective of transaction cost theory[10], market orientation theory and consumer value had been adopted in the researches in related fields[11]. In a review work, further research directions were pointed out, among which "what offerings generate more profit" and "which segments are more attractive" were included[12]. These interesting topics can be inherited by the discussions on launch strategy in e-commerce[13]. It can be inferred that how to launch new products may also mean significantly to the lottery-like culture creative products, such as blind-box of course. Hence, this research will use "new product launch" as a control variable when discussing the uncertainty of customer purchase in order to exclude the certain part of the influences from scheduled business activities.

2.3. Rationality in data selection

Uncertainty has been an interesting topic in the discussion for marketing strategy[14], such as the findings on homogenizing heterogeneous consumers and separating heterogeneous consumers[15]. If the researchers are expecting research findings with great practical significance, detailed data is required. A review work pointed out the increasing emphasis on big data analytics (BDA) in e-commerce in recent years[12]. But it does not necessarily mean that every research should make use of all data simultaneously. Instead, big data require the combination of countless detailed data, such as Schroeck argued for the use of data fusion which combines various less reliable data sources in order to create a more precise and worthwhile data point[16]. Hence, this research will use the first-hand original data from business practice. Similar studies focusing on details of a single brand or store include the study on UGC and MGC[17]. Especially, the study on sales forecasting and analysis model for commodities with common characteristics using their historical sales data through time series model has offered implications to this research[18].

In addition, lots of exiting studies had concluded treasurable experiences that transaction or business activity data should be paid great attention, including structured data from retail transactions, customer profiles, distribution frequency and volume, product consumption and service usage, nature and frequency of customer complaints. These researches include: (1) United Parcel Service (UPS) examines usage patterns and complaints to predict customer defection[19]; (2) Wal-Mart persuades its suppliers to monitor product movement by store to help plan promotions, store layout, and reduce stockouts[16]; (3) Amazon engages a type of predictive modeling technique called collaborative filtering, using customer data to generate 'you might also want' prompts for each product bought or visited. Amazon revealed at one point that 30 % of sales were generated through its recommendation engine[20]; (4) Harrah's, the US hotels and casinos group, compiles detailed holistic customer profiles and uses them to customize marketing in a way that has increased customer loyalty[20]; (5) Progressive Insurance and Capital One are conducting experiments on a regular basis to segment their customers systematically and effectively and to personalize product offers[20]; (6) Wal-Mart developed Retail Link, a tool that presents its suppliers with a view of the demand in its stores so suppliers know when stores should be restocked rather than waiting for an order from Wal-Mart stores[20].

Based on previous experiences, the variables and data collection in this research can be considered as valid.

3. Research Design and Research Data

According to official news, the first infector appeared in Beijing on January 20th[21], labeled as 142 in timeline, which is regarded as the starting point for the epidemic period in Beijing. Figure 1 shows the changes in sales income and sales volume before and during epidemic time, and dashed lines indicate workdays during the week. Considering that most people start their social activities for weekend from Friday evening, Friday is defined as weekend together with Saturday and Sunday.

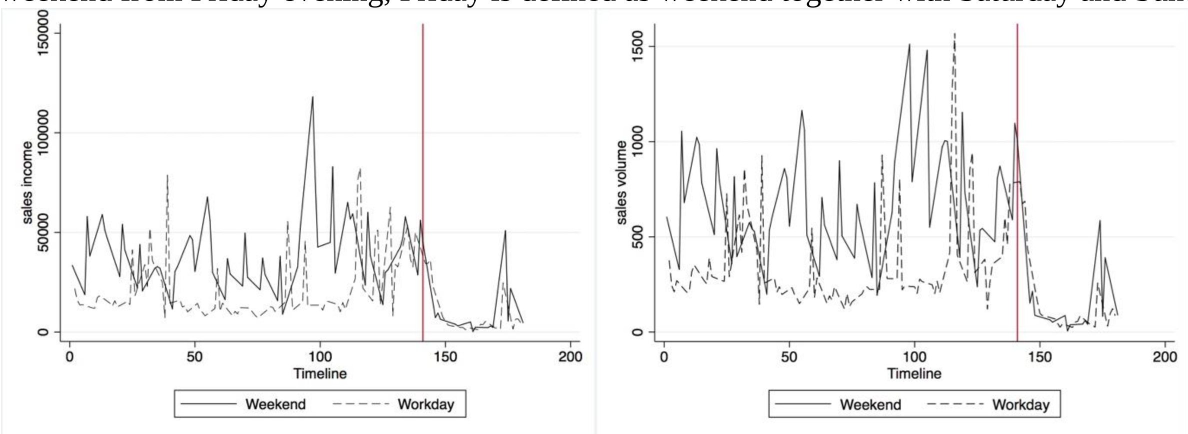

Figure 1: Sales Income and Volume.

In epidemic time, indicated by the vertical line in Figure 1, sales income and volume both dropped dramatically, which are contributed totally by online sales. Still, there are some spikes in the end of February, although the coronavirus' risk still exists. Consequently, it is even convincible that customer demands on culture creative products and/or services might face potential opportunities even in special times. Moreover, a rebound in market demand can also be expected[22]. The key point for companies to seize such opportunity is to figure out how customer demands changes.

3.1. Research Design

The daily data on the business performances of these blind-box stores are collected, covering September, 2011 through February, 2020. Totally 182 days but with minor missing variables. After data preprocessing, 176 pieces of valid data are selected for further analysis.

Daily sales income is strongly dependent on customer flow and the volume of products been sold during the day. Expression is given as Equation 1. Considering customer follow on weekends and commercial event days are normally are higher than weekdays, control variables are also put into the regression model in Equation 1.

$$\text{Sales Income}_i = ß_{11} \times \text{Sales Volume}_i + ß_{12} \times \text{Customer Flow}_i + ß_{13} \times \text{weekend}_i + ß_{14} \times \text{event}_i + e_{1i} \quad (1)$$

According the regression model, a predict value of sales income for each single day (day i) can be given. There is a difference between predict value and real value. All these differences reveal the sales incomes that cannot be explained by existing variables. For each single day, such difference can be regarded as the impulsive contribution/impact from customers' purchasing behaviors, which may vary due to public or private affairs. In this research, it is regarded as "purchase uncertainty".

In this research, in order to study consumption-rebound after epidemic time, it is necessary to discover how customer behavior varies before and after epidemic period's starting point. Especially for such culture creative products, customers' offline behavior may be depressed due to the decrease in outdoor activity, but on the other hand, their desire in obtaining new product will not disappear. Consequently, their purchasing behaviors form the key factor for the impulsive impact on sales income mentioned above.

One typical indicator been used for measuring daily performance of each store is "volume of products in each transaction". Consequently, second stage regression analysis will be conducted. Using the residual from first stage regression model as dependent variable, and using variable "ldl" (volume of products in each transaction)" as main independent variable, as well as control variable "new" (whether new product is launched), second stage regression model is designed as Equation 2.

The impact from variable "ldl" (volume of products in each transaction) worth further discussion. In increase of ldl indicates that one customer is buying more items at one time. But it is also possible that customers tend to buy more cheap items at one time instead of purchasing lots of expensive products simultaneously. Consequently, "ldl2" (ldl square) is also put into Equation 2.

$$\text{Residual} = ß21 \times \text{ldli} + ß22 \times \text{ldl2i} + ß23 \times \text{newi} + ß24 \times \text{ldli} \times \text{newi} + \text{e2i} \quad (2)$$

3.2. Research Data

This research makes use of the daily business performance data from a culture creative company in Beijing, starting from July, 2019 to February, 2020, totally 182 samples that labeled from 1 to 182 in timeline. Variable names and types are listed in Table 1. Descriptive statistics of all variable is given in Table 2. In order to run t-test to make detailed comparisons between different days, the data for the five channels of payment are also included.

Table 1: Key Variables for Regressions in the Research

Variable Name	Label	Type	Variable Name	Label	Type
weekend	Weekend or not	Discrete 0/1	event	Commercial event	Discrete 0/1
new	New product launched	Discrete 0/1	cro	Epidemic period	Discrete 0/1
holiday	In holiday or not	Discrete 0/1	-	-	-
kll	Volume of customers per day	Continuous	ldl	Volume per transaction	Continuous
vol	Sales volume	Continuous	sales	Sales income	Continuous

Table 1: Variable Description.

variable	mean	sd	min	p25	p50	p75	max
cash	948.9	947.9	-300	206	591.5	1514	4353
point	1206	3431	0	78	260	692	23496
mobile	2673	7226	0	0	118	1099	49462
bankcard	4501	11561	0	109	677	1935	71275
QR-code	2876	6405	0	0	0	1955	31141
kll	156.6	120.5	2	71	114	249	501
ldl	3.190	2.510	1.400	2.200	2.500	3.100	26.60
vol	429.8	336.8	6	198	291	622.5	1570
sales	25464	20751	246	10285	16822	36858	118066

4. Descriptions to the Business Data and T-tests

From Figure 1, for sales income and sales volume, obvious decreases in epidemic period can be observed. The t-tests labeled by “cro” shown in Table 3 show that when it came to epidemic time, daily sales income dropped to 8943 from 30099 averagely, at significant level of 0.001. Daily sales volume dropped from 508 to 157. For each channel of payment, cash, membership point and bankcard all dropped significantly.

Hypothetically speaking, the decrease in offline customer flow (kll) may trigger an increase in online shopping, which may be the reason for the insignificant increases in mobile and QR code channel, increased by 1918 and 1058 separately.

Another interesting finding that support the research design of this paper is that the volume per transaction (ldl) in epidemic period did not drop, but increased by 1.507, approximately 52.6%, comparing with normal times. This is a persuasive sign for the potential opportunity for culture creative markets of this kind. Since customer’s psychological demand will not diminish, their purchasing behavior may change a little bit due to the limits on outdoor activities. These behaviors and their changes may be the key to discover why daily sales shift up and down. Consequently, empirical analysis based on two-stage OLS regression will be conducted.

Table 2: T-test for variables

Variables	cro			event			holiday			weekend		
	0	1	Mean Diff	0	1	Mean Diff	0	1	Mean Diff	0	1	Mean Diff
cash	1103	397.9	705.549***	890	1639	-748.822***	874.1	1657	-783.173***	623	1396	-773.489***
point	1435	385.2	1049.441*	1099	2465	-1366	1236	919.5	316.6	850.3	1688	-837.9
mobile	2250	4169	-1918	2778	1452	1326	2872	801.4	2071	2582	2800	-217.4
bankcard	5655	385.9	5269.167**	4090	9314	-5224	3975	9482	-5507.404*	4484	4524	-40.07
qr	2644	3702	-1058	2999	1430	1570	3114	618.5	2496	2516	3370	-853.9
kll	190.2	36.9	153.304***	149.8	236.9	-87.095***	152.2	198.2	-45.95	108.4	222.8	-114.359***
ldl	2.863	4.369	-1.507***	3.227	2.796	0.431	3.239	2.755	0.484	3.15	3.251	-0.101
vol	507.6	156.8	350.709***	416.4	598.5	-182.069*	420.5	517.1	-96.61	319.3	585.8	-266.554***
sales	30099	8943	21156.011***	24184	40448	-16263.742***	25130	28622	-3493	19122	34173	-15051.254***

5. Empirical Findings based on Regression Analysis

The correlation matrix of all variables is given in Table 4, but only the key variables will be discussed further in the regression analysis. Before moving on to regression analysis. There are some interesting findings that might have some practical implications to store managers. Among all channels of payment, sales income that contributed by cash does not have significant correlation with those contributed by membership-point and mobile channel such as Alipay and Wechat. Though it is commonly acknowledged that how one customer chooses the way of payment does not influence others, income from bankcard channel is positively correlated with cash and membership-point. It may be inferred that stores can possibly enhance promotion activities through collaboration with banks, such as direct discounts, coupons or membership's special offers.

Table 3: Variables' Correlation Matrix.

	cash	point	mobile	bankcard	qr	kll	ldl	vol	sales
cash	1								
point	0.12	1							
mobile	0.047	-0.044	1						
bankcard	0.297^{***}	0.175^{**}	-0.115	1					
qr	0.226^{***}	-0.062	0.551^{***}	-0.132^{*}	1				
kll	0.744^{***}	0.247^{***}	-0.013	0.434^{***}	0.117	1			
ldl	-0.146^{*}	0.132^{*}	0.480^{***}	0.013	0.115	-0.159^{**}	1		
vol	0.687^{***}	0.325^{***}	0.111	0.508^{***}	0.152^{**}	0.895^{***}	0.118	1	
sales	0.594^{***}	0.423^{***}	0.262^{***}	0.478^{***}	0.180^{**}	0.810^{***}	0.218^{***}	0.957^{***}	1

Significant level: * 0.1, ** 0.05, *** 0.01

Since overall sales income is the total sum of income from all channels, it is not necessary to put each channel as variable into the regression model. Instead, volumes of customer flow and how each customer makes decisions when purchasing are more important. Sales volume is strongly significantly correlated with sales income (0.957^{***}). But since products are priced differently, it is still put into the regression model but it is not necessary to set it as a new dependent variable since all stores care more about income.

5.1. First Stage Regression Analysis

Table 4: Regression on Sales Income.

	(1)	(2)	(3)	(4)	(5)
0.weekend	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
1.weekend	$1.5e+04^{***}$	-1.3e+03	-917.415	-481.989	-542.117
	(5.21)	(-1.33)	(-0.43)	(-0.49)	(-0.56)
0.event	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
1.event	$1.6e+04^{***}$	118.221	4116.674	739.542	325.695
	(3.06)	(0.07)	(1.18)	(0.45)	(0.20)
vol		56.359^{***}		63.163^{***}	68.169^{***}
		(39.81)		(22.27)	(20.14)
kll			139.552^{***}	-22.897^{***}	-8.726
			(15.78)	(-2.75)	(-0.89)
vol × kll					-0.024^{***}
					(-2.61)
_cons	$1.8e+04^{***}$	1118.167	3670.724^{**}	1380.059^{*}	-416.457
	(9.33)	(1.55)	(2.41)	(1.93)	(-0.42)
N	178	176	178	176	176
adj. R2	0.164	0.914	0.654	0.918	0.920

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Table 5, five regression models are tested (VIF<3), with Model (1) as null model. Taking customer flow into consideration, as model (3), adjusted R2 increased from 0.164 to 0.654. Due to the potential collinearity between sales income and volume, model (2) have a high level of adjusted R2. After adding customer flow into model (2), though it is still significant in model (4), its sign is changed from positive in model (3) to negative in model (4). Further, interaction item of sales volume and customer flow in model (5) shows that sales volume's impact on overall sales income may be weaken when customer flow increase, which means negatively moderated.

Model (5) have a high level of adjusted R2. Still, there exists a gap between predicted value and real sales income. For normal days, such differences can be omitted. In this special time, understanding how customers behave abnormally has significant meanings to companies. Predicting cannot help company improve performances, especially after epidemic time. Understanding how customers' unpredictable purchasing passion are influenced seems to be of more help.

5.2. Second Stage Regression Analysis

Consequently, using the residuals from model (5) as dependent variable, named as purchase uncertainty, model (6) through (12) are given in Table 6.

Model (6) is null model containing only control variable "new", which indicate if there is new product been launched. Considering that customers' passion and interests towards new products will possibly last for a while after launching, and customer flow has strong collinearity with variable "weekend" and "event", it is reasonable to infer that new products' impact on customer passion lasts for averagely 3 days, just the length of weekend. Consequently, variable "new" is set to "2" if new product been launched on that day, while "3" and "4" indicate the second and third day after new product's launch. "1" indicates all other normal days with no new product been launch. Note that even for holidays longer than 3 days, the last few days are treated as normal days for variable "new" in this research. The negative coefficients in model (6) show that comparing with the first day of new product launch customers purchase impulse drops in the following days.

Model (7) contains volume per transaction (ldl), which has positive impact on purchase uncertainty though with a low level of significance. For common sense, customers may generally be more likely to either buy more products with lower price or buy less products with higher price because of totally budged restriction. Consequently, square item of variable "ldl" is introduced in model (8), but the result shows that it does not have significant impact on purchase uncertainty.

Model (9-11) discuss the moderation effects of variable "new" on "ldl", while model (9) is for the entire duration and model (10) and (11) are for pre- and post-epidemic period respectively. Before the epidemic period starts, result in model (10) shows that customer behaviors do not fluctuate according to new products' launch. Customers may be so excited at new products' launch that they go for shopping immediately when the products are available. For those who are busying working, they may go at any time when convenient. Consequently, the sales performance on the second day of new products' launch may not be as good as expected, which explains the statistics in model (10) that "new=2" is negatively moderating "ldl" while all other moderators are insignificant.

When it comes to epidemic period, some customers are required to work or study at home, which means their times are more flexible. Meanwhile, shopping malls are also under strict flow control. Hence, they may tend to make more purchases at one time, especially when new products attract their attention, just as demonstrated by the statistics from model (11). Variable "ldl" is strongly significant and with a greater value comparing with model (9), which is for the whole period. Moderating effects from "new" are all negative. But similar as model (7), square item of "ldl" still needs to be discussed, which is been verified in model (12).

Model (12) is also for epidemic period, the variable "ldl" and its square item are all significant and it is negatively moderated by the variable “new”. The result shows that lower or higher “ldl” can better contribute to purchase uncertainty, which indirectly help increase sales income.

Taking R2 into consideration, this research tends to treat model (9) and (12) to be convincible, which have the best explanatory power for the whole time and for epidemic period respectively.

Table 5: Regression on Purchase Uncertainty.

	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1.new	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2.new	-4.1e+03**	-3.7e+03**	-3.6e+03*	242.941	3901.619	2.8e+04***	1.3e+04***
	(-2.24)	(-2.01)	(-1.96)	(0.09)	(0.73)	(5.02)	(3.36)
3.new	-2.6e+03	-2.1e+03	-2.1e+03	1402.132	1.3e+04	1.2e+04***	3094.287
	(-1.41)	(-1.11)	(-1.13)	(0.51)	(1.22)	(4.12)	(1.35)
4.new	-3.5e+03**	-2.9e+03**	-2.9e+03**	-2.3e+03	1246.898	1.4e+04***	3109.174
	(-2.50)	(-2.07)	(-2.05)	(-1.14)	(0.25)	(7.03)	(1.59)
ldl		287.174*	-218.257	513.604**	1778.633	1149.555***	-3.2e+03***
		(1.70)	(-0.50)	(2.17)	(1.37)	(11.57)	(-5.19)
ldl2			23.866				143.690***
			(1.26)				(7.07)
1.new × ldl				0.000	0.000	0.000	0.000
				(.)	(.)	(.)	(.)
2.new × ldl				-1.1e+03*	-2.3e+03*	-6.0e+03***	-2.4e+03*
				(-1.91)	(-1.66)	(-3.22)	(-1.89)
3.new × ldl				-1.0e+03*	-5.8e+03	-1.0e+03***	1192.999***
				(-1.66)	(-1.34)	(-3.49)	(3.32)
4.new × ldl				-80.257	-1.2e+03	-612.706***	1861.539***
				(-0.21)	(-0.89)	(-3.56)	(5.08)
_cons	3096.641**	1715.971	2900.064	627.349	-2.8e+03	-1.7e+04***	-1.8e+03
	(2.39)	(1.13)	(1.62)	(0.37)	(-0.59)	(-9.04)	(-0.73)
N	176	176	176	176	137	39	39
group	all	all	all	all	cro = 0	cro = 1	cro = 1
adj. R2	0.022	0.033	0.036	0.049	0.029	0.804	0.924

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusions

6.1. Practical Implications

When the threat from coronavirus start to mitigate, people’s social activities including consumption for physical and mental leisure will also rebound. Identifying the significant differences between normal time and epidemic time can help firms better seize the opportunities for business growth in recovery stage. Conclusively, the following implications may be helpful for practices.

Firstly, though sales volume and customer flow are both treated as extremely important by most stores, the result in model (3-5) shows that the two factors are balancing each other. On one hand, sales volume cannot increase without higher customer flow, which means the two factors have collinearity to some extent. On the other hand, shopping experience may be negatively influenced when customer flow increases, which means customer follow is negatively moderating sales volume’s influence on sales income. For stores, in order to achieve better sales performance, attracting and guiding customers should be within appropriate extent. For example, due to inventory and productivity limitations, monthly customer flow cannot increase for more than 2841 if the store cannot provide 1 more blind-box product.

Secondly, this research recommends that further efforts on managing purchase uncertainty are the key to sales improvement, especially in this special time. According the statistics from regression analysis, model (12) offers good explanation to purchase uncertainty in epidemic period. Volume of items per transaction (ldl) has quadratic impact on the fluctuation of purchase. When such uncertainties exist on each transaction, stores should try to adjust their promotion tactics for the purpose of leveraging “ldl” distribution among all customers in order to maximize overall sales. Further calculation based on the model (12) shows that 11-12 items per transactions seems to be a pitfall. Comparatively, the corresponding control point for pitfall is normally 4-5 items, though model (8) is not persuasive enough. However, practical implications can be possibly made. On one hand, blind-box supply in epidemic times may drop simultaneously as customer flow decreases. Consequently, maximizing the value-add effect of each product seems to be even more important. On the other hand, stimulating customer purchase to be, for example less than 4 or higher than 16, avoiding 11-12 anyway, seems to be a good promotion tactic.

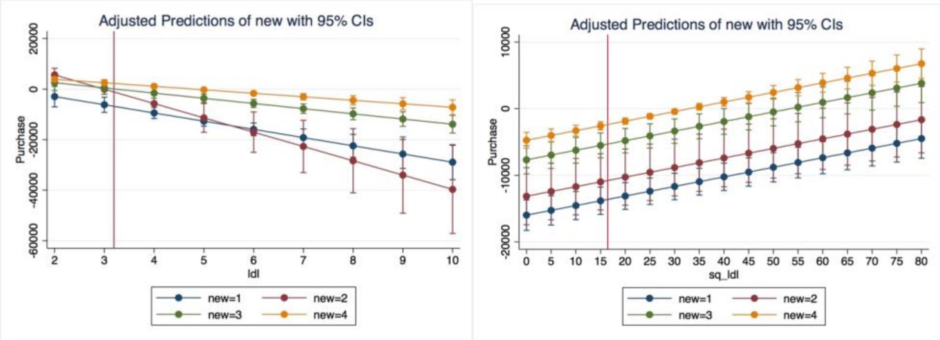

Figure 1: Marginal Effects’ Differences from New Launch Days.

Further implications on promotion tactics is new product launch. Figure 2 show the moderating effects from launch days. The vertical line is the mean value of “ldl” and “ldl2”. The figure on the right shows that the trend of moderating effect on “ldl2” remains the same for all days, but the negative moderation becomes weak after new product’s launch day. Yet, such minor change does not have much influence on the decision making on promotion tactics or strategies. The figure on the left indicates that the moderating effects vary according to days after new launches. On the day of new launches, the marginal influence “ldl” has on purchase uncertainty is negative and keeps increasing. But from the second day after launches, the marginal influences start from positive and turn into negative after “ldl” passes its average value 3.19. Especially the second day’s marginal influence drops more rapidly. Though the marginal influence from “ldl” changes a little bit, considering also the impact from “ldl2”, the precise quantitative advices to predict purchase uncertainty in business practice can be made based on the result from this research.

6.2. Discussions

This research focused on the blind-box market, which is quite popular in recent years, and made use of the business data covers both before and after coronavirus’ arrival and made quantitative analysis using OLS regressions. Unfortunately, since there were not enough researches discussing lottery-like culture creative product such as blind-box and there was not any similar circumstance as the coronavirus in the year 2019 and 2020, the supports from existing literatures are limited. However, the models in this research provide persuasive supports for both academic research and practical business management. The most meaningful innovation of this research is that it introduced a new perspective, which is purchase uncertainty. It can help firms manage their business in a more effective way. But on the other hand, this research still has limitation. Blind-box companies are not too much in number and business data are too sensitive to be published. Consequently, this research only includes the data collected from the stores of the most famous and popular firm, which means though it is convincible that the research can reflect the market to a large extent but it may not be precise for all firms. That is to say, when using the models in this research to help make decisions on business planning or promotion, it will be better to be used in a maneuverable way. Conclusively, this research has its theoretical and practical contributions, based on which further attempts on purchase uncertainty can be discussed. Similar methods and models can also be introduced to the discussion on other culture creative markets, especially in the time of economic recovery after epidemic period.

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