温州肯恩大学
WENZHOU-KEAN UNIVERSITY

The Adoption of Online Catering and the Substitution Effect of Online and Offline Consumption under the Shock of COVID-19: Evidence from China's 'Meituan.'

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by

Chen, Dan

1098117

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Abstract

Extreme events significantly impact consumption, an essential part of the national economy. COVID-19 has undoubtedly hit China's industry hard, including offline catering and tourism. However, it has also made some online sectors thrive. This study uses data from Meituan quarterly financial report from 2017 to 2021, using Eviews and Python to standardize and normalize the data. Then, the vector error-correction model (VECM) and the multiple linear regression model are applied to test the hypothesis. First, the adjustment coefficient and estimated coefficient are used to observe the changes trend of online catering channels after the COVID-19 intervention. Then, the substitution effect from offline to online was assessed using the multiple linear regression coefficients. The epidemic's impact led to significant setbacks in the industry at that time, and consumption also decreased to varying degrees. However, if adjusting fluctuations in overall consumption, online catering channels are more widely adopted after the epidemic intervention. Also, there is a positive substitution effect from offline to online due to the COVID-19. The research results provide suggestions for the catering industry marketers to optimize the operation strategy and timely increase online channels to withstand the impact of the sudden outbreak.

Keywords: COVID-19, Online Consumption, Offline Consumption, Catering Industry, Multiple Linear Regression, Vector Error-Correction Model

Introduction

China and even the world have undoubtedly suffered the heaviest blow during the sudden outbreak of the virus. McKibbin and Fernando (2020) noted that China has suffered from a contraction in production and restrictions on transportation. And importantly, there were market anomalies because some of the panics among consumers and businesses were distorting traditional consumption patterns.

During the Novel Coronavirus outbreak in January 2020, many containment policies were put in place requiring people to stay at home for social security reasons. Once consumers' mobility is restricted, online channels are the only way to consume. And in the future, for the sake of safety or policy restrictions, people will reduce unnecessary risks through online shopping. What's more, food is a necessity for people to survive. How will people's consumption patterns change in the context of COVID-19 intervention? Is there an opportunity for the development of online catering? Therefore, this paper will study the epidemic's impact on the changing trend of online catering consumption and whether there is a sizeable increasing role.

Hypothesis I: The COVID-19 intervention had an impact on online catering, and the role of online catering has risen.

In addition, due to the long isolation time at home and social environment changes, consumers have gradually changed their preference in choosing consumption channels. For example, whether they like to go to restaurants (can communicate with friends, can

feel the offline service of the staff) to online shopping (avoid contact with people, more safety and hygiene). Therefore, when people start to worry about the safety risk of offline dining, whether there is a positive substitution effect from offline to online, whether people gradually prefer online consumption to offline consumption.

Hypothesis II: The COVID-19 intervention caused the substitution effect between online and offline channels.

The main contribution of this paper is to find out whether there is an increase in the adoption of online channels after the epidemic intervention. Also, this paper estimates whether there is a behavioral change in consumers' preference for online channels, which fills the literature gap on proposing the substitution effect of online and offline in the catering industry. The empirical results of this paper reveal the changing trend of online consumption and the substitution effect of online and offline consumption after the epidemic and help Chinese catering enterprises fully understand this changing trend to optimize their future market development and loss prevention strategies. Therefore, this paper has significance for guiding catering industry operators under the unstable epidemic situation.

The rest of the paper is mainly divided into four parts. First of all, through reviewing the existing literature, the hypothesis that I want to study and the applicable data or model are determined. Part 2 introduces methodology in detail, including collecting and processing data, the primary VEC model, and multiple linear regression models. Then, Part 3 evaluates the results in particular by studying the coefficients of

each model and making tables and figures. The final part provides the conclusions drawn by the study and the contributions and limitations provided.

Literature Review

This article aims to show how offline and online food markets are changing in the shock of COVID-19. Grasping the trend of the different food channels will help marketers timely change their future development strategies and prevent losses when the epidemic strikes again. This article cites 15 literature that helps us understand the changes in consumer behavior and the development of online food channels from a global perspective and within China, and the substitution effect of online and offline food channels in China. This literature review aims to delve deeper into the impact of COVID-19 on the food industry from global to internal China.

The impact of the COVID-19 pandemic on food channels in global

A sudden outbreak has led to significant changes in consumption patterns around the world. As Watanabe and Omori pointed out, online services involving face-to-face communication have declined significantly in Japan, while consumption and services through e-commerce are increasing. They used credit card transaction data to explore whether online spending will continue to grow even after COVID-19 recedes and whether consumers will revert from online spending to offline spending (Watanabe & Omori, 2020). They predict that consumers' behavioral tendencies have been altered, as some other researchers have, Moon, Choe, and Song. They found that since late 2019, the COVID-19 virus has wreaked havoc in South Korean society, resulting in many aspects of consumers' daily lives being exclusively online. Therefore, they analyzed the characteristics of consumers using offline shopping channels during the pandemic and

the determinants of choosing online or offline shopping channels after the pandemic (Moon, Choe, & Song, 2021). The method they used was mainly in the form of online questionnaires. Although this had some limitations, the frequency of online and offline shopping channels provided by participants could help them better understand the changes in consumers' consumption patterns after the epidemic.

In addition, the German food market has changed dramatically. Four researchers (Dannenberg, Fuchs, Riedler, & Wiedemann, 2020) pointed out that the COVID-19 pandemic has led to a dramatic increase in online transactions. They aimed to analyze the extent to which online grocery retail has expanded during the pandemic and why. And they showed an upward trend in the grocery trade in general, with disproportionately high growth in the online grocery trade, yet a slight shift from grocery stores to electronic grocery stores. This finding has given me some inspiration for my subsequent research. Despite the outbreak of the epidemic, offline channels cannot be replaced entirely due to factors such as technology and population distribution. Still, there is a substitution effect between online and offline channels.

The impact of the COVID-19 pandemic on consumer behavior in China

It's not just foreign food markets that are being disrupted. China is also facing different challenges. To prevent the further spread of COVID-19, the Chinese government has imposed quarantine policies and travel restrictions. Therefore, people's consumption patterns may be subtly changed. A study was conducted on the factors influencing the change of people's consumption patterns due to COVID-19 shock

(Filimonau, Beer, & Ermolaev, 2021). It tested the relationship between the dependents by establishing a multiple regression model. Once consumers' consumption patterns are changed to a large extent, the catering industry will suffer huge setbacks. How to achieve survival under the considerable impact is worth thinking about now. Therefore, Kim and Wang examined the factors that influence the financial turnaround of catering companies to achieve sustainability after large-scale closures. They used sales data from a total of 86,507 small and medium-sized catering businesses in nine cities in mainland China to identify factors that minimize uncertainty in different business closures and restrictions (Kim, Kim, & Wang, 2021). However, the blockade for a long time also led to changes in Chinese consumers' preferences for the catering industry, such as environmental sanitation and service methods. Therefore, Zhang, Jiang, Jin, and Chen discussed the impact of COVID-19 on China's catering sector in 5 cities and analyzed and predicted consumers' preferences. This study showed that after the outbreak, consumers paid more attention to changes in dishes, dining environment, and epidemic prevention and control. Parcels and takeaways are also on the rise (Zhang, Jiang, Jin, & Chen, 2021).

The rise of online food in the COVID-19 pandemic in China

As the saying goes, "Food is the life of the people." Changes in consumer behavior trends caused by offline channel closures during the pandemic are bound to drive the development of online food channels. In the literature of Guo, Liu, Shi, and Chen, we can intuitively understand the rise of e-commerce. They explore whether and, if so, why

and how e-commerce can ensure food supplies for city dwellers (Guo, Liu, Shi, & Chen, 2020). Moreover, four researchers (Gao, Shi, Guo, & Liu, 2020) also argued for the former hypothesis. They used the Wuhan outbreak as an example, finding that the proportion of confirmed COVID-19 cases increased the likelihood that consumers would buy food online. It is more likely to happen for younger people who live in big cities and are less risky to shop online. This paper will contribute to the government's support and supervision of the food safety network.

Additionally, evidence from another study also supported the rise of online food channels under COVID-19. With most consumers avoiding restaurants and other public places, home cooking became the norm. Therefore, the increase in takeout e-commerce and the online purchase of some fresh agricultural products have also significantly increased. Chang and Meyerhoefer studied how epidemics affected demand for online food shopping services by using data from Taiwan's largest agricultural e-commerce platform (Chang & Meyerhoefer, 2020). The study found that consumer demand for these online agricultural products increased, and the variety of products sold on e-commerce platforms increased accordingly. It also means that increased online demand is driving sales of niche products.

Hypothesis I: The COVID-19 intervention had an impact on online catering, and the role of online catering has risen.

The substitution effect of online food channel and offline food channel

Since COVID-19 was first detected in China in 2019, due to strict measures to contain the spread of the virus, people's lifestyles and consumption habits have been severely affected. The frequency of online shopping increases, and online shopping replaces offline and face-to-face dining. But will this phenomenon continue in the food market? Yue, Liu, Zheng, and Wang studied the changes in Chinese consumers' food consumption on vegetables and meat and their willingness to pay (WTP). Yue et al. found that consumers' consumption price index was positively influenced by the expected duration of COVID-19, direct contact with infected persons, and income (Yue, Liu, Zheng, & Wang, 2021). Therefore, we can find that the rise of online marketing channels may not stop, as consumers are willing to share the costs caused by the epidemic.

However, Xu, Gao, and Zhang contradicted the previous one by presenting new evidence related to the previous discussion. They used the panel data of the high-frequency payment system to build a regression model. They estimated the substitution effects from offline channels to online channels by regressing the online consumption and offline consumption on the year and before/after the Lunar New Year's Day indicator (Xu, Gao, & Zhang, 2021). Their findings showed that online markets are more resilient than offline ones. However, offline catering has specific properties that online channels cannot imitate, so the online market cannot replace the offline market. Therefore, due to different data and research tools used in the two pieces of literature,

it is still necessary to conduct further research on whether the offline food market will flourish as expected.

Hypothesis II: The COVID-19 intervention caused the positive substitution effect between online and offline channels.

To sum up, many research results show that epidemic intervention does have a series of significant impacts on the catering industry. Still, all discussions on the impact results remain to be tested. There are few studies on the existing literature on the substitution effect between online and offline channels in the Chinese catering industry. This study attempts to investigate the development of online catering and the substitution effect of online and offline channels in the catering industry before and after the epidemic by taking the Meituan platform as the research object to fill this research gap.

Methodology

Data

The study's data comes from Meituan, a sizeable Chinese service platform. I can find the turnover of each quarter in Meituan's annual financial report from Q3 2017 to Q2 2021, including online catering and offline services. There are several advantages in my data: First, as Meituan is a large platform with a broad audience and dense geographical coverage, I can take it as the research object to study the development of the online catering industry under the influence of the epidemic. Compared with other platforms or companies, it is easier to get micro online and offline data. Second, it isn't easy to use online payment data to determine whether it is an online catering service because it may be due to e-commerce transactions. Meituan has unequivocal financial statements for online and offline catering, which is not affected by online payment. Thirdly, many offline restaurants do not provide online services. In contrast, the Meituan platform, as a gathering platform for restaurants of different sizes and tastes, includes both online and offline service channels. Therefore, these data can exclude deviations in consumers' dietary preferences and only focus on the impact of COVID-19 on the choice of online or offline channels.

To analyze my data, I did the following processing to make them more standard and normative. First, I needed to eliminate the deviation of the overall decrease in consumption after the epidemic—for example, the decline in consumption of the entire restaurant industry caused by the reduction in income. Therefore, I introduced monthly

CPI (Consumer Price Index), GDP (Gross domestic product), and China's catering industry revenue as reference values. Second, most of the macro data collected are quarterly data, so to observe more intensive cyclical fluctuations, I used Eviews software to convert the quarterly data into monthly data. Third, the variables collected are of a very different unit magnitude, leading to a significant bias in the results that affect the conclusions. Therefore, I used Python to normalize all the data I have collected. Here, I used the z-score standard method to eliminate the deviation of the unit difference. Finally, fluctuations in the consumer price index (CPI) are also skewed. CPI reflects the volatility of prices, implying inflation or deflation of the Chinese economy before and after the outbreak. Therefore, to avoid the impact of price fluctuations on the goods, I adopted standardized consumption data instead of the raw data; all the data are shielded from the effects of CPI fluctuations. After processing the data through these steps, the data I obtained can genuinely reflect consumer preferences for online and offline channels before and after the epidemic.

The VEC model

An autoregressive distributed lag (ARDL) model and vector error-correction (VECM) model were used to investigate COVID-19 related shock on crude oil prices and global food price indices (Musa et al., 2020), analyzing the significant or negative relationship between the impact of the pandemic and price movements. In this study, I used the vector error-correction model (VECM) with cointegrating variables to determine the influence of COVID-19 shock on online food consumption. It is a robust

model for proving my Hypothesis I, which can help me avoid the fluctuations of the whole catering industry consumption before and after the epidemic, focusing on consumers' preferences between online and offline channels. As the advantage of this model shows, the cointegration term is known as the error correction term, which gradually corrects the deviation from the long-term equilibrium through a series of partial short-term adjustments.

Lütkepohl (2006) mentioned in his structural guide that the vector autoregression (VAR) model can simulate the dynamic structure of time series variables and can be rewritten as VECM. Therefore, first of all, I used the VAR model with 24 lags to represent the standardized monthly online consumption before and after COVID-19, as is shown in Equation (1):

$$\mathrm{y_t} = a + \emptyset_1 \mathrm{y}_{t-1} + \emptyset_2 \mathrm{y}_{t-2} + \cdots + \emptyset_{24} \mathrm{y}_{t-24} + \varepsilon_t \quad (1)$$

where y_t denotes the full-time series of the standardized monthly online consumption for both 2019 and 2020. $\emptyset_1, \emptyset_2, \cdots, \emptyset_{24}$ are the parameters. a represents intercepts.

Similarly, I also used the VAR model with 24 lags to represent the whole Chinese catering industry standardized monthly consumption before and after COVID-19, as is shown in Equation (2):

$$\mathrm{x_t} = b + \theta_1 \mathrm{x}_{t-1} + \theta_2 \mathrm{x}_{t-2} + \cdots + \theta_{24} \mathrm{x}_{t-24} + \varepsilon_t \quad (2)$$

where x_t denotes the full-time series of whole Chinese catering industry standardized monthly consumption for both 2019 and 2020. $\theta_1, \theta_2, \cdots, \theta_{24}$ are the parameters. b represents intercepts.

Then, considering a constant and a linear trend, and assuming a cointegration relationship between online consumption (as shown in Equation 1) and total consumption in the whole catering industry (as shown in Equation 2), I can rewrite it into the VECM form, as is shown in Equation (3):

$$\Delta y_t = \alpha\beta y_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\tau_i} \Delta y_{t-i} + \mathrm{v} + \delta \mathrm{t} + \varepsilon_t \quad (3)$$

where $\boldsymbol{\tau_i}$ = -$\sum_{j=i+1}^{j=p} \emptyset_j$. The Δy_t denotes the full-time series of the standardized monthly online consumption with a cointegration term $\mathrm{x_t}$. α represents the adjustment coefficients in short-run equations (Cointegration relation is not considered). β represents the parameters in the cointegration equations. δt implies a quadratic time trend at the data level because we usually want to include a constant or linear movement in the equation. v and ε_t in (1) and (3) are identical.

After the VEC model is well established, the p-value and coefficient can explain my hypothesis very intuitively. There are two adjustment coefficients on L._ce1 (as shown in Table 1) are the parameters in the adjustment matrix for this model. According to the respective the p-value and adjustment coefficients α, I can estimate the tendency and speed of adjustment of one variable to the other between two interdependent variables. Additionally, after considering the cointegration relation for this model (as shown in

Table 2), there are estimated parameters, including coefficients β, standard error, and the p-value. If the coefficient β is below 0, the increase in the standardized online consumption is more significant than the increase in the standardized catering industry consumption before and after COVID-19. Therefore, due to the epidemic intervention, the role of online catering in 2020 has increased compared with that in 2019. Otherwise, the negative β implies the role of online catering in 2020 has decreased compared with that in 2019.

The Multiple Regression Model

Multiple regression models were used to analyze the intervention of COVID-19 on consumption (Jung & Sung, 2017), to estimate the respective substitution effects of online and offline consumption in different service categories under the shock of COVID-19, and to predict and suggest the development trends of various production and service industries in China. I am also interested in substitution between online and offline catering consumption at different time points. Here, to test Hypothesis II, I compared the standardized consumption differences between online and offline before and after the COVID-19 by formulating the regression model.

To determine the impact of the COVID-19 intervention on substitution effects of online consumption and offline consumption after the COVID-19, I obtained D_t (Equation 4) when the standardized consumption values in the online and offline over the same period are contrasted. Then, I regressed the standardized consumption differences on two indicators that represent specificity by year (Equation 5):

$$D_t = \text{Online}_t - \text{Offline}_t \quad (4)$$

$$D_t = \omega + \lambda_1 * I_t + \lambda_2 * GDP + \varepsilon_t \quad (5)$$

where t represents the different months. D represents the standardized consumption differences between online and offline after the COVID-19. I_t represents total catering industry standardized consumption after the COVID-19. GDP is a control variable that refers to a reference indicator of earning power in different periods. The ω represents the intercept that measures the fixed consumption difference. λ_1 reflects the relationship between the standardized consumption differences and the whole catering industry's standardized consumption after the COVID-19.

Similarly, I modeled the standardized consumption differences before the COVID-19 in the same way, as is shown in Equation (6):

$$d_t = \mu + \gamma_1 * I_t + \gamma_2 * GDP + \varepsilon_t \quad (6)$$

where t represents the different months. d represents the standardized consumption differences between online and offline before the COVID-19. I_t represents total catering industry standardized consumption before the COVID-19. GDP is a control variable that refers to a reference indicator of earning power in different periods. μ represents the intercept that measures the fixed consumption difference. γ_1 reflects the relationship between the standardized consumption differences and the whole catering industry standardized consumption before the COVID-19.

After the Multiple Regression Models are well established, the p-value, regression coefficient, and correlation coefficient can intuitively explain my Hypothesis II. The substitution effect can be reflected by comparing D_t and d_t, which measures the increase of online consumption compared to offline consumption in each time period in 2019 and 2020 respectively. Also, I compared λ_1 and γ_1 to observe the relationship between consumption difference and total consumption before and after the epidemic. If there is a positive substitution effect from offline consumption to online consumption, the absolute value of λ_1 is larger than that of γ_1. Otherwise, there is a negative substitution effect.

The degree of substitution effect

The previous model helped me test whether the epidemic intervention impacted substitution effects and determine the effect trend. To get an accurate degree of the substitution effect, I compared the online standardized consumption changes from 2019 to 2020 (as is shown in Equation 7) with offline standardized consumption changes in the same month from 2019 to 2020 (as is shown in Equation 8). This model can eliminate the consumption bias caused by seasonal changes, especially the high consumption during The Spring Festival and other holidays. When the changes of standardized online consumption and the changes of standardized offline consumption are contrasted, I obtained the degree of substitution effect, as is shown in Equation (9):

$$\text{Online\_c}_t = \text{Online}_{2020,t} - \text{Online}_{2019,t} \quad (7)$$

$$\text{Offline\_c}_t = \text{Offline}_{2020,t} - \text{Offline}_{2019,t} \quad (8)$$

$$\varphi_t = \text{Online\_c}_t - \text{Offline\_c}_t \quad (9)$$

where t represents different months. Online_ c_t refers to the changes of standardized online consumption from 2019 to 2020. Offline_c_t refers to the changes of standardized offline consumption from 2019 to 2020. φ_t refers to the degree of substitution effect from offline to online each month due to the COVID-19 intervention. If φ_t is positive, it reflects that the epidemic's impact caused substitution effects from offline to online, and the absolute values represent the degree.

As I mentioned before, consumers' income will change due to the epidemic, which will affect their consumption in the catering industry. Therefore, instead of the changes in online consumption that I used in my last model, I used the changes in the income elasticity of online consumption (as shown in Equation 10). Here, the income elasticity of online consumption refers to the amount of online consumption that consumers are willing to spend for every 1 unit increase in consumption in the catering industry and can be obtained by dividing online consumption by total catering industry consumption. I modeled the changes in the income elasticity of offline consumption in the same way (as is shown in Equation 11). The degree of substitution effects from offline to online in this model is shown in Equation (12):

$$\text{Online\_EIc}_t = \text{Online\_EI}_{2020,t} - \text{Online\_EI}_{2019,t} \quad (10)$$

$$\text{Offline\_EIc}_t = \text{Offline\_EI}_{2020,t} - \text{Offline\_EI}_{2019,t} \quad (11)$$

$$\rho_t = \text{Online\_EIc}_t - \text{Offline\_EIc}_t \quad (12)$$

where t represents different months. Online_EIc_t refers to the changes in the income elasticity of online consumption from 2019 to 2020. Offline_EIc_t refers to the changes in the income elasticity of offline consumption from 2019 to 2020. ρ_t refers to the degree of substitution effect from offline to online each month due to the COVID-19 intervention.

If ρ_t is over 0, it reflects that the epidemic's impact caused positive substitution effects from offline to online after considering the volatility of consumption throughout the whole catering industry. The absolute values represent the degree. Otherwise, if ρ_t is below 0, there are adverse substitution effects from offline to online due to COVID-19 intervention.

Results

The online consumption changes due to the epidemic

The main result is derived from the vector error-correction model (3), which exams the speed and trend of adjustment between interdependent variables (online consumption and total catering consumption). Additionally, it estimates the trend of online consumption after adjusting the cointegration term. Table 1 & 2 and Figure 1 & 2 display the relevant results, which helped me intuitively analyze the changing trend of online consumption due to the COVID-19 intervention.

In Table 1, the estimated coefficient on whole catering industry consumption in the cointegrating equation is statistically significant, as are the adjustment parameters. The adjustment parameters in this table imply a tendency to adjust to another variable. The estimate of the adjustment coefficient [D_y_t]L._ce1 is 0.034. Thus, when the whole catering industry consumption is too high, the online consumption quickly adjusts toward the whole consumption level when the whole catering industry consumption is adjusting. Also, the estimate of the adjustment coefficient [D_x_t]L._ce1 is 0.087. Thus, when the online consumption is too high, the total catering industry consumption quickly adjusts toward online consumption level while online consumption is adjusting. Here, there is a positive adjustment trend between these two interdependent variables, and [D_x_t]L._ce1 is more significant than [D_y_t]L._ce1, suggesting that the adjustment speed of the whole catering industry consumption is faster than that of online consumption.

TABLE 1 Adjustment coefficients and associated intercepts of VEC Model

Parameters	D_y_t	D_x_t
Adjusted α	0.034***	0.087**
_cons	0.031	-0.012

*** p<0.01, ** p<0.05, * p<0.1

In Table 2, the estimated coefficient β represents the changing trend of the independent variable after adjusting the cointegration term. After adjusting, the estimated coefficient on online consumption is 1, and the estimated coefficient on the whole catering industry consumption is -4.649. In other words, when I assume that online consumption is a linear time-series graph with a slope of 1, the whole catering industry consumption is a linear time-series graph with a negative slope. Therefore, when β is below zero, it implies that the growth of online consumption is much higher than that of the whole catering industry consumption. It means that online consumption is playing an increasing role due to COVID-19 intervention, and its growth trend is much higher than that of total consumption.

TABLE 2 Estimated coefficients of VEC Model in the cointegrating equation

Parameters	D_y_t	D_x_t
Estimated β	1	-4.649***
_cons		0.148
Standard Error		1.203

*** p<0.01, ** p<0.05, * p<0.1

Ramsey et al. (2021) compared the vertical price movements of the meat market to the model predictions. They evaluated that COVID-19 related shock on price is temporary, suggesting the resilience of meat market supply. Figures 1 & 2 indicate that the COVID-19 shock to the online consumption and the whole catering industry

consumption have a transitory effect. Still, the difference is the interval to which they fluctuate in response to a pandemic intervention. In these two figures, the abscissa is the various months from 2019 to 2020, totaling 24 periods. I found that both online consumption and the whole catering industry consumption tended to be around the equilibrium at the beginning of 2019. Still, both experienced a sudden decline at the end of 2019 and the beginning of 2020, soon recovered or even exceeded the equilibrium, and gradually recovered to the equilibrium in the second half of 2020. Although online consumption and the whole catering industry consumption dropped to -5, online consumption rebounded to 10 after the epidemic intervention, while the whole catering industry consumption only rebounded to 5. Therefore, the epidemic shock did impact online consumption, and after the epidemic intervention, online consumption showed a more significant upward trend compared to that of the overall consumption. Online consumption plays a more important role under the COVID-19 intervention.

FIGURE 1 The time-series of online consumption

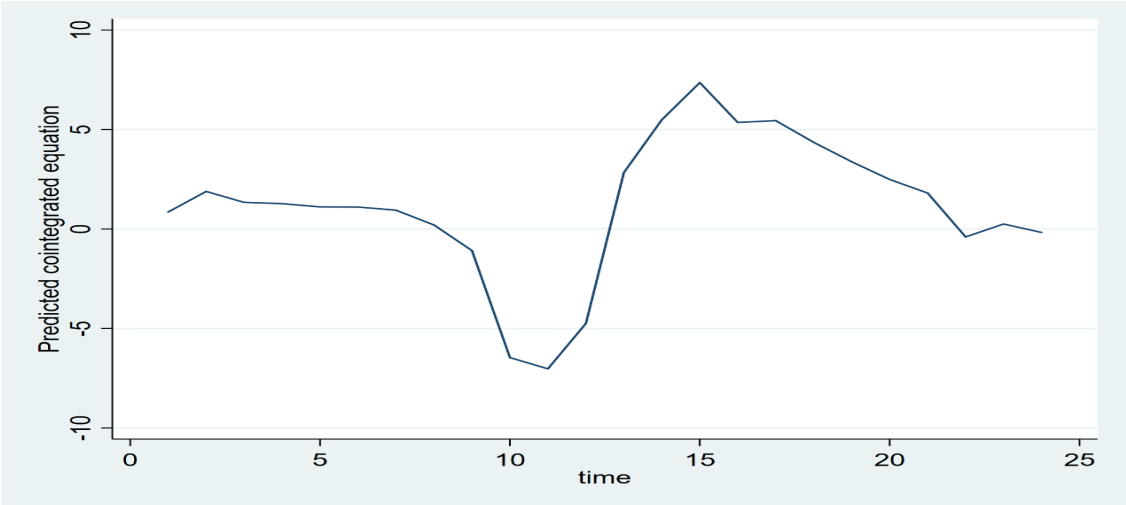
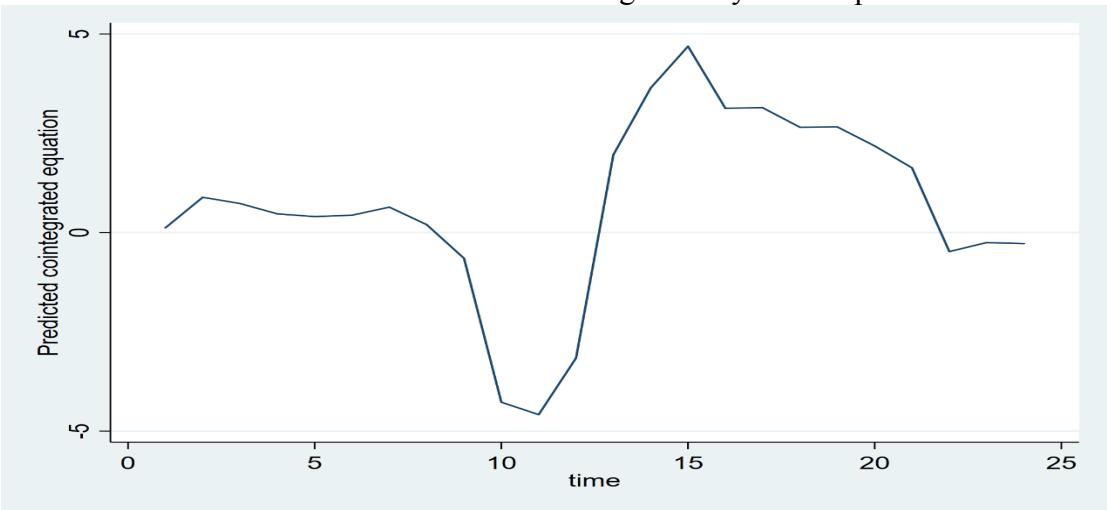


FIGURE 2 The time-series of the whole catering industry consumption



The substitution effect of online and offline food consumption

The main result is derived from the regression models (5) and (6), examining whether the epidemic intervention produced a positive substitution effect from offline consumption to online consumption.

Table 3 & 4 provides the summary of descriptive statistics and correlations between four variables. The negative correlation between Dt and It implies that the difference between online and offline consumption is large to small when the whole catering industry consumption is small to large. After the epidemic, the total consumption of the catering industry declined, while the difference between online consumption and offline consumption increased. Therefore, the decline of online consumption was smaller than offline consumption after the epidemic. In other words, if I consider that people's preferences for food are separated, either online or offline, there may be a positive substitution effect from offline to online, as in my hypothesis II. The following tables and figures will further test my hypothesis.

TABLE 3 Descriptive Statistics

Variable	Observation	Median	Std. Dev.	Min	Max
Dt	48	-.06	.31	-.78	.57
CPI	48	-.08	1.01	-2.1	2.54
GDP	48	-.005	1.01	-1.76	2.33
It	48	-.07	1.01	-2.73	2.07

TABLE 4 Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) Dt	1.00			
(2) I	-0.48***	1.00		
(3) GDP	-0.13	0.74***	1.00	
(4) CPI	-0.06	-0.35*	-0.28*	1.00

Table 5 tests the results from the multiple regression model using two different periods (before and after COVID-19), considering the role of the epidemics on the relationship between the consumption differences between online and offline and the whole catering industry consumption. Column (1) represents the relationship result based on the period before and after the COVID-19 when the influence of other control variables is not considered. Column (2) represents the relationship result based on the period before and after the Covid-19 when the power of other control variables is considered. According to this table, there is a negative relationship between consumption differences and the whole catering industry consumption. However, the absolute value of the regression coefficient after the epidemic is larger than that before the epidemic. As a result, the difference between online and offline consumption fluctuates more in the period after COVID-19. In other words, when the epidemic first broke out, although total consumption fell, there was a positive substitution effect from

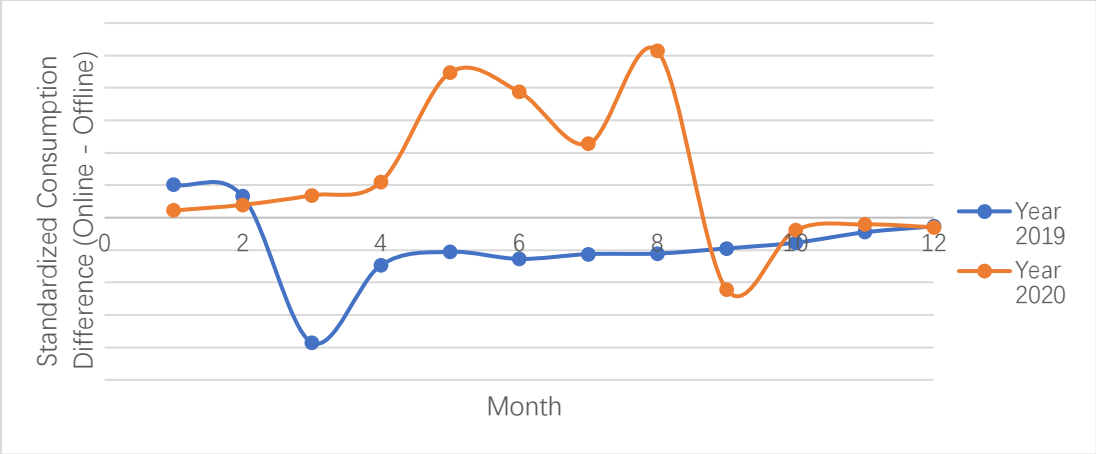
offline to online. And, as the whole catering industry consumption slowly recovered, this substitution effect gradually weakened, as is shown in Figure 3.

TABLE 5 Main Regression Results: Covid-19 Effect

Dependent Variable	Before Covid-19		After Covid-19	
	(1)	(2)	(1)	(2)
I	-0.125***	-0.0782*	-0.0580***	-0.268***
	(0.0201)	(0.0445)	(0.0137)	(0.0392)
GDP		-0.00968		-0.0416
		(0.0465)		(0.0384)
CPI		-0.0630*		0.234***
		(0.0349)		(0.0565)
Constant	-0.143***	-0.144***	0.380***	0.217***
	(0.0149)	(0.0254)	(0.0221)	(0.0354)
Observations	30	30	12	12
R-squared	0.560	0.625	0.570	0.919

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

FIGURE 3 The standardized consumption difference between online and offline



Figures 4 & 5 evaluate the results from the models (9) and (12) by using two different methods (whether to account for fluctuations in overall consumption), considering the COVID-19 intervention on the degree of the substitution effect to varying periods of the year. Although there are some differences in the fluctuation of a

substitution effect between the two methods, they both follow the same rules. The substitution effect peaks in the middle of the year but decreases and returns to a stable state as the epidemic abates.

FIGURE 4 The substitution effect from offline to online in 2020 (Method I)

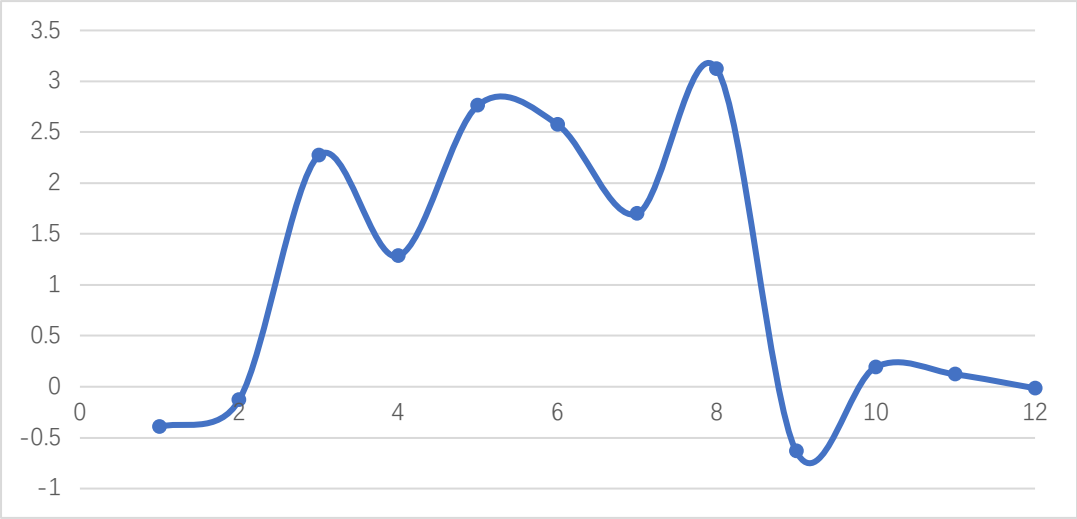
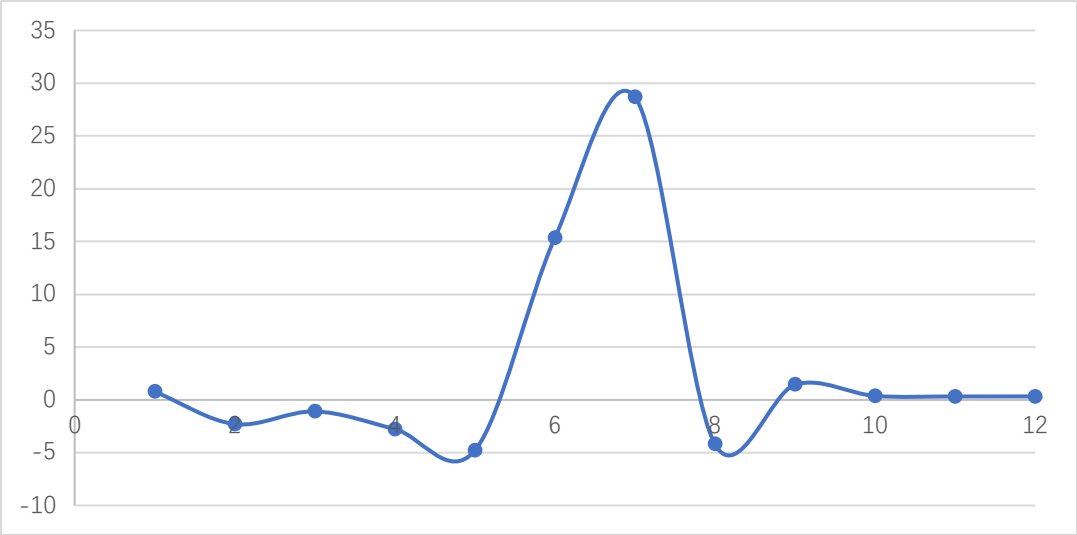


FIGURE 5 The substitution effect from offline to online in 2020 (Method II)



Conclusion

This paper takes the Meituan as the primary research object to explore the impact of the epidemic intervention on online consumption and the substitution effect from offline to online. In addition, the vector error correction (VEC) model with cointegrating terms and multiple linear regression model are applied to test the trend and degree of influence, and the following conclusions are finally drawn:

1. COVID-19 intervention had a positive impact on online consumption, under which the growth trend of online consumption was greater than that of the whole catering industry consumption. In other words, after avoiding the changes that consumers are willing to spend in the catering industry before and after the epidemic and only considering the preference for online or offline channels, online channels will play a more important role after the epidemic. However, it is worth noting that with the post-epidemic adjustment and recovery, the positive impact of online consumption will slowly return to a stable state.

2. COVID-19 intervention produced positive substitution effects from offline to online, regardless of considering the fluctuations in overall income and consumption or not before and after the pandemic was averted. A positive substitution effect will occur when consumers consume less during the outbreak, as consumers quickly adjust from offline consumption to online consumption. As the epidemic slowly recovers, the substitution effect will gradually diminish until stabilizes. Therefore, offline channels can't be replaced, but online channels can be good strategies when the epidemic hits.

Contribution and Limitation

This paper can provide valuable suggestions for the catering industry marketers and the government by providing statistical analysis and empirical test results. The results show that the significant adoption of online consumption and the positive substitution effect from offline to online will gradually weaken to the initial stable state during the recovery of the post-epidemic period. However, the epidemic is not entirely over, as all consumers and restaurant operators now fear. If there is another outbreak in one city at a certain point, it will affect all the surrounding towns. The ideal situation of a full recovery of the epidemic is not easy to emerge. And, consumers' consumption behavior preference is also changed subtly. Therefore, while not replacing offline channels, the study calls on catering industry operators to develop online channels for timely preventing loss in the face of epidemic outbreaks. At the same time, the government should improve security and privacy systems such as online payment to conform to the development of online channels.

Additionally, due to the difficulty in collecting data of some micro variables and incomplete information on the economy, catering industry, and market, this study has some limitations:

1. The collected data representing online and offline consumption are quarterly data, which cannot accurately reflect the specificity of each month's consumption. Due to the limitation of data, it isn't easy to accurately estimate the starting point of the substitution effect's rise, but only its interval can be determined. In addition, the

substitution effect suddenly decreased in September, and there is no reasonable explanation to explain the reason for the sudden decline of the substitution effect.

2. Only Meituan Platform is taken as the research object, implying the restricted consumers and catering industry operators. Although Meituan is a food delivery platform with many users, it does not serve every consumer or restaurant. Therefore, it isn't easy to accurately reflect the situation of the whole Chinese catering industry.

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