The variations in individual consumption change and the substitution effect under the shock of COVID-19: Evidence from payment system data in China

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\textbf{Abstract}

Over the last two decades, scholars have pointed to the significance of the impact of extreme events on consumption, a prominent part of national economies. How does the COVID-19 epidemic influence consumption? Using high-frequency payment system panel data, we explicitly consider the individual consumption changes and the substitution effect between online and offline markets of multiple categories by constructing autoregressive integrated moving average (ARIMA) models and conducting regression analyses. The $p$ value and regression coefficients of the substitution elasticity are used to estimate the changes and the substitution effects from the offline to the online channels. The results show that consumption saw a remarkable decline after the surge of COVID-19 in 2020 compared to 2019. Overall, online markets were more resilient than the offline markets and the substitution effects after the epidemic's outbreak between the online and offline markets were significant for one-third of the consumption categories. However, the online market could not replace the offline market for some categories due to the product characteristics. The vulnerable industries in the face of the epidemic's intervention are determined as being traditional catering, transportation, tourism, and education, and the shortage of healthcare services in extreme events is also pointed out. The results provide suggestions for policies on targeted enterprises and public service.
1 | INTRODUCTION

Extreme events such as infectious diseases are devastating to the economy. The COVID-19 epidemic has lasted for more than 10 months and is still spreading across the world at present. The shock from COVID-19 has raised concerns about the macroeconomy. Compared with other macroeconomic factors, the impact of the epidemic outbreak is qualitatively different (Jung et al., 2016). The outbreak forces governments where the infection risks are high to place restrictions on the transportation of people and goods. Therefore, outdoor activities are reduced during the spread of infectious diseases (Kim, 2015; Sung, 2016) and in turn, the epidemic’s impact on the economy might increase (McCloskey & Heymann, 2020).

Individual consumption plays a critical role in boosting the economic growth. Consumption comprised as much as 70% of Gross Domestic Product (GDP) in the United States (U.S.) (Muellbauer, 2020) and 58% in China in 2019 (Wang, 2020), the largest and second-largest economies in the world. In public health emergencies, the development of consumption is largely related to consumers’ internal psychology. The spread of the epidemic and the increasing mortality rate will cause panic and the fear of an unknown deadly virus is similar in its psychological effects to the reaction to biological and other terrorism threats and causes a high level of stress (Hyams et al., 2002). People worry about life safety and uncertainty about the epidemic situation, which will affect their consumption behavior. The epidemic situation's continuous development leads to people's decisions to cut back on consumption and further exacerbates the size of the recession caused by the epidemic (Eichenbaum et al., 2020).

China was affected by the COVID-19 epidemic in the early stage of the outbreak and was the first country to implement the lockdown policy, which has been reckoned as having severely impacted household consumption (Cai, 2020). The related research has concentrated on the impact on GDP (Barro et al., 2020) and has estimated the economy's short-term, medium-term, and long-term trends based on forecasting models (Bloom et al., 2005), but they did not consider the actual consumption of different categories and channels. Furthermore, such events’ impact should be studied on a high-frequency basis, such as semi-monthly, rather than using monthly or quarterly data (Galbraith & Tkacz, 2013). Some studies on previous public health emergencies focused on the total burden of epidemics based on low-frequency data and did not reach meaningful conclusions. Only a small temporary impact of several extreme events in Canada on consumer behavior was found, on account of low-frequency data (Galbraith & Tkacz, 2013).

Our research aims to contribute to the literature from two aspects. First, it adds to current knowledge by elaborating individual consumption changes after the COVID-19 outbreak based on high-frequency panel data of actual purchases. Our daily transaction data spans from 4 weeks before the epidemic to 12 weeks after it and it is possible to reveal the changes in a short period afterward. Second, we compare the substitution effect from the offline channel to online channel for multiple categories to contrast their differences in the face of the intervention. This comparison is conducive to analyzing the resilience and vulnerability of categories, further guiding marketing decisions, both in the public and private sectors.

The article proceeds as follows: We review the literature on the impacts of epidemics on consumption and pose two hypotheses in Section Two. We then describe the empirical case background, method, and data used to conduct the empirical analysis in Section Three. In the fourth section, we present the results and, finally, we discuss the findings and address the conclusions and limitations and outline the agenda for future research.
2 | LITERATURE REVIEW

2.1 Heterogeneity of the impacts of epidemics on consumption categories

The total economic losses or consequences of epidemics to outbreak-affected areas are generally recognized and well documented, but the variations among categories and market channels need further study. By changing expectations and deterring investment, epidemics can interfere with short-term economic outcomes (Bloom & Canning, 2006). The 2014 Ebola epidemic in West Africa imposed a regional economic burden of U.S. $53 billion in social and economic losses (Huber et al., 2018). Due to the disruption to consumption itself and the jump in income insecurity, U.S. real consumer spending in the second quarter of 2020 could fall by around 20% if household labor income falls by 16% (Muellbauer, 2020). The disruption of epidemics might even play a role in reducing the $1.08 billion in merchandise exports in unaffected countries under the global economy's background (Kostova et al., 2019). The above studies confirmed the negative impact of epidemics on the macroeconomy. However, the considerable disruption of an epidemic on consumer spending is highly heterogeneous, concerning market segments and channels.

First, the influence of epidemics on consumption varies between categories with some being resilient, whereas others are vulnerable. Tourism is very sensitive to crises as it shows a characteristic of sensitivity and fluctuation (Wen et al., 2005). Hotel bookings dropped during SARS (Chen et al., 2007; Pine & McKercher, 2004) and tourists tended to choose inexpensive rooms during a financial crisis (Song et al., 2011). The stock prices of accommodation and traditional catering experienced large declines in March 2020 (Huang et al., 2020). In contrast, there was no statistically significant impact of the airborne virus, the Middle East Respiratory Syndrome (MERS), epidemic on grocery consumption (Jung & Sung, 2017). Not surprisingly, a positive and significant effect on pharmaceutical firms' stock returns was discerned from 2003 to 2014 due to dangerous infectious diseases (Donadelli et al., 2017). Moreover, the demand for insurance products might be stimulated by disasters (Chang & Berdiev, 2013).

Existing studies focused on the performances of a few specific categories, and they were studied individually, especially high vulnerability industries such as tourism (Papatheodorou & Pappas, 2017; Pine & McKercher, 2004) or the variation of one consumption category under the shock of different types of disaster (Chang & Berdiev, 2013). Lu et al. (2020) conducted surveys into the performances of the small and medium-sized enterprises after the COVID-19 intervention according to three industries, but they did not divide the enterprises into different categories. The comparison between multiple consumption categories under the shock of one epidemic is still scarce to date. This paper aims to contrast the changes in multiple consumption categories in the period before and after the social isolation enforcement measures due to the COVID-19 intervention.

2.2 The substitution effect between the online channel and the offline channel

The magnitude of the substitution elasticity in consumption has long received attention relating to its link with the attitude toward risk (Hahm, 1998). Substantial literature has discerned the heterogeneity of substitution elasticity degrees between durables and non-durables (Campbell & Mankiw, 1991; Cashin & Unayam, 2016; Hall, 1988). Over the last two decades, the substitution between market channels has drawn attention because online shopping has become more popular in recent years. Unlike traditional physical markets, the internet offers the opportunity for electronic marketing (Wang
et al., 2013) so that consumers have access to both offline and online shops (Jung & Sung, 2016). Variations in the degree of substitution across categories were also detected, for instance, sales of the print edition of the Washington Post were reduced due to the introduction of a digital version (Gentzkow, 2007). In contrast, an online shopping service’s introduction had a limited cannibalization effect on offline sales (Pozzi, 2013). If two forms of consumption are substitutes, a rise in one results in a fall in another due to crowding-out. If they are complements, an increase in one would amplify another (Auteri & Costantini, 2010).

In academia, online and offline markets have been compared from the perspective of consumers’ behaviors and preferences, such as brand loyalty, price sensitivity, and price dispersion across channels (Brynjolfsson & Smith, 2000; Chu et al., 2010; Danaher et al., 2003; Zhuang et al., 2018). However, limited research efforts have been undertaken to explore whether the substitution effect varies among categories during and after disease outbreaks.

Moreover, the shock of epidemics might trigger a behavior change, with customers being less sensitive to prices and brand, but more concerned about safety. Online shopping has an advantage over offline shopping, especially in epidemic outbreaks, because it avoids unnecessary crowds gathering and reduces the possibility of virus spread compared with offline consumption. Some scholars argue that due to the market’s alternative shopping channels, an external shock no longer results in a change in total consumption (Jung & Sung, 2017), which could be interpreted as a substitution effect and is true for some categories. For instance, the offline consumption of electronic products fell by 7.9%, while online consumption rose by 7.03% during the MERS outbreak in South Korea (Jung & Sung, 2017). To date, existing studies are limited to a small number of categories and are not able to systematically investigate the change in the substitution effect between channels after an extreme event. Thus, the variation in the substitution effect among multiple categories in a short period after an epidemic remains unrevealed.

Moreover, an inappropriate choice of instruments or inadequate consumption measures might lead to weak results or biased estimators (Cashin & Unayam, 2016; Hahm, 1998). The online and offline samples were collected separately in related research and such data might mix shopping behavior differences across customers with shopping media (Chu et al., 2010). Our study is based on a within-subject comparison, allowing us to separate the online market’s effects from consumer-specific effects. Channel-specific behavior differences related to product characteristics will be investigated as we observe the total individual expenditure. In addition, the natural experiment presented by the outbreak of COVID-19 avoids the problem of weak instruments.

2.3 The variability of the consumption changes in different phases of interventions

The last concern is the variability of the consumption change in different phases of interventions and the differences between ex-ante estimation and ex-post empirical data. In the first phase, the continuous development of the epidemic situation leads to people’s decisions to cut back on consumption (Eichenbaum et al., 2020). In the later phase, when the epidemic is under control, people need not reduce social interaction for the sake of personal security. As a result, the economy will rebound and recover (McKibbin & Fernando, 2020) leading to the disparity between the estimations and the reality, and between estimations. During the most severe SARS period, it was estimated that the epidemic would reduce China’s GDP by 1.5% (Hanna & Huang, 2004). However, because the control of the virus in China was better than expected, the epidemic only reduced GDP by about 0.5%.
It was estimated that the COVID-19 pandemic would reduce the world GDP, or that of the typical country, by six or more per cent in the first half of 2020 (McKibbin & Fernando, 2020; Oxford Economics, 2020). The COVID-19 intervention's impact on different consumption categories in China has also been studied based on the estimations. A 1% increase in the severity would cause a 10.57% decrease in productivity according to a forecasting model (Norouzi et al., 2020). The Organisation for Economic Co-operation and Development (OECD, 2020) assumed that spending on transport services and private vehicles would decline by one-half and spending on recreation, hotels, and restaurants would decline by three-quarters. What was worse, all expenditure on clothing and footwear, furnishings, and household equipment and personal care services would stop completely. The above ex-ante analysis needs to be verified by actual purchase data.

Moreover, individual consumption change in different phases varies between market channels. Shopping in crowd places will not recover until the late phase of an epidemic. It took 2 months for offline luxury consumption to recover after the MERS epidemic, while online consumption remained unchanged (Jung & Sung, 2017). Thus, the substitution effect between online and offline channels might fluctuate in different phases, which would only be detected by high-frequency data.

In an effort to fill the aforementioned gaps, we differentiate the COVID-19 intervention's impact on 15 consumption categories for online and offline channels with empirical evidence. We also examine the substitution effects of these categories and contrast them on the timeline using high-frequency data.

In this article, we hypothesize the following:

Hypothesis 1 The changes in the consumption after the COVID-19 intervention vary among categories and market channels.

Hypothesis 2 There is a substitution effect between the online and offline markets after the epidemic outbreak. The effects are diverse among consumption categories due to product characteristics.

3 | METHODS AND DATA

This section illustrates the payment data collection and measurement strategies for online and offline consumption of 15 categories. We attempt to quantify the consumption fluctuations by examining consumers' expenditures, measured utilizing payments.

3.1 | Study area and background

3.1.1 | The spread of COVID-19

The first case of COVID-19 in Wuhan was reported in December 2019 and the city went into lockdown on January 23rd. A central leading group on battling the COVID-19 epidemic was established on January 25th, the first day immediately after the Lunar New Year's Eve, and 30 of 34 provincial-level administrative regions initiated first-level public health emergency responses. Thus, travel, business meetings, and other social interactions have been minimized. China's travel restrictions could delay importing cases into cities unaffected by the COVID-19 outbreak, buying time to coordinate an appropriate public health response (Chinazzi et al., 2020). Eighty million people did not return to work until February 10th and most people worked from home in the first phase of the outbreak.
Twenty-one provinces lowered the emergency response levels as of March 4th. Regional transportation restrictions were lifted in mid-March across the country, which was the sixth or seventh week after the Lunar New Year's Eve. Therefore, the first phase spanned from the Lunar New Year's Day to early and mid-March, whereas the second phase started from early and mid-March.

3.2 | The Lunar New Year's Day in China

The COVID-19 outbreak coincided with the Lunar New Year's Day in 2020, the most important holiday in China. Usually, people have a family reunion on the Lunar New Year's Eve (like Christmas Eve or Thanksgiving Eve in Western countries) and stores are closed from the Eve to the third day of the Lunar New Year. Generally, citizens prepare presents for friends and relatives and stockpile foods and necessities for the first week after the Lunar New Year's Eve. Therefore, they do a lot of shopping 1 or 2 weeks before the Lunar New Year's Eve and, in most cases, they book their travel or accommodation in advance of the Golden Week as well. The first week immediately after the Lunar New Year's Eve usually sees a remarkable decline in consumption, whereas it recovers gradually thereafter.

3.3 | Data

Our data comes from the largest payment system in mainland China: the Union Pay personal card database. In 2019, there were more than 1,000 million individual cardholders and 7 billion personal cards issued by over 400 institutions. Consumers’ payment behavior in China has changed in recent years as, for convenience and safety, more and more people have become used to paying electronically, such as swiping a debit card or card or using online or mobile banking instead of paying in cash since 2000. The Union Pay's share is around 79% of the total payments for more than 30 cities. The database records each purchase across all consumption categories. This daily data set contains detailed information for each transaction, including the date, payment amount, store name, and payment channel, that is, online and offline. This paper uses the data set that includes consumption information at two time points: 2019 and 2020. The Union Pay data set is exploited to accurately categorize merchants according to the product and service provided by enterprises and public institutions: traditional catering, tourism and accommodation, retail trade, health care, transportation, construction materials, stationery and digital products, luxury goods, utilities and public service, entertainment and sports, clothing and bags, education, financial services, commercial services and maternal, and infant supplies and services. The merchants’ categories are identified according to their registered scope of business.

Several benefits can be easily identified. First, the payment system data are recorded electronically and instantaneously, and measured accurately, including debit card, credit card and all the mobile payments, such as Alipay and WeChat Pay, bound with a personal bank card; second, reliable consumption statistics are available on a daily frequency, so that subtle change is discernible; third, the economic activity in each category is captured rather than aggregated to a total amount. The category-level analysis allows us to study the consumption in merchants across sections and, therefore, purchases provide a valuable high-frequency indicator of consumption expenditure (Galbraith & Tkacz, 2013). Still, there are some limitations to this data set. It does not include cash-based consumption, and payments made with an account on Alipay or WeChat pay are also missing.

Second, some emerging apps might mix the consumption category, such as Didi (the same as Uber), Meituan (an app that provides a delivery service for restaurants and consumers), and Dingdong
Grocery (an app that sells daily groceries with a delivery service). Consumers’ payments are categorized to these companies, but the consumptions are transportation, catering, and retail rather than commercial services. For instance, a passenger might call a traditional taxi through the Didi Platform and make the payment on the app. Although the platform would pay the driver later, the passenger’s payment is recorded under the name of Didi Platform and classified as a commercial service.

3.4 | Method and statistical analysis

To analyze our data, first, we studied the outcome variable in standardized values to circumvent the following problems. First, Union Pay's share is around 79% in total consumption, but it varies across categories and might change between years. In addition, the fluctuations of the consumer price index (CPI) and disposable income could yield bias as well. The CPI was around 105 in the first quarter of 2020 and the disposable income for the first quarter rose by 0.8% compared to 2019. To address these issues, we used standardized consumption data instead of raw data. The standard value is the average daily payment amount from the first Sunday to the second Saturday in the same year. Then, to remove the day-of-the-week effect observed in the unfiltered raw data, we used each week’s average daily consumption to denote the amount of consumption for the week. Lastly, we compared the consumption in 2019 and 2020 according to the lunar calendar, to remove the seasonal variation bias, especially the Lunar New Year Golden Week. We matched the data from 4 weeks before the COVID-19 intervention to 12 weeks after it and the same period in the last lunar year, that is, from December 28 2019 to April 18 2020 and from January 8 2019 to April 30 2019.

3.4.1 | The ARIMA model

To determine the influence of COVID-19 intervention, an autoregressive integrated moving average (ARIMA) model is used in this study. It is a statistically robust model for proving our hypotheses as the analysis is related to a time series and we know the intervention’s timing. The ARIMA or AR model was used to analyze the MERS intervention on consumption in South Korea (Jung & Sung, 2017), to predict the trend of the incidence of COVID-19 (Benvenuto et al., 2020) and to estimate China’s energy and electricity demand patterns in pandemic conditions (Norouzi et al., 2020). In addition, linear regression is used to evaluate consumption changes in the period before and after the COVID-19 intervention. The methodology is well-established, and the $p$ value and coefficients can have intuitive interpretations.

We used the ARIMA model for both 2020 and 2019. ARIMA ($p = 5$, $d = 1$, $q = 0$) is selected as the best ARIMA model for standardized average daily consumption in 2020 and is shown in Equation (1)

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} + \phi_5 y_{t-5} + \epsilon_t$$

where $y_t$ denotes the full time series of the standardized average daily consumption in 2020. $\phi_1$, $\phi_2$, $\phi_3$, $\phi_4$, and $\phi_5$ are the parameters.

ARIMA ($p = 0$, $d = 0$, and $q = 4$) is selected as the best model for standardized average daily consumption in 2019 and is shown in Equation (2)

$$x_t = b + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} + \theta_4 \epsilon_{t-4} + \epsilon_t$$
where $x_t$ denotes the full time series of standardized average daily consumption in 2019, $\theta_1$, $\theta_2$, $\theta_3$, and $\theta_4$ are the parameters.

Then, when the fitted values in 2020 and 2019 are contrasted, we obtained $d_t$ (Equation 3) and regress $d_t$ on an indicator of before or after the Lunar New Year’s Day (Equation 4)

$$d_t = \hat{y}_t - \hat{\tilde{y}}_t$$  

$$d_t = \beta_0 + \beta_1 I(t > t^*) + \epsilon_t$$  

where $t^*$ is the indicator for the Lunar New Year's Day.

If the regression coefficient is below 0, the decrease in the standardized average daily consumption in 2020 compared to that in 2019 is larger for the days after the Lunar New Year’s Day than before it. Otherwise, the decrease is smaller for the days after the Lunar New Year's Day in 2020.

### 3.4.2 The degree of substitution elasticity

The substitution elasticity between goods is constant at each time point (Quaas et al., 2020), but might change between periods. We are interested in substitution between the online and offline markets for each category at the same and different points of time. We compared the consumption differences before and after the COVID-19 intervention in 2020 and the same period in 2019 according to the lunar calendar to measure the substitution effect of online and offline consumption. Since the online and offline markets sell the same products or provide the same services, we assume that preferences over online and offline markets are separable for a given category. For each consumption category, we ran a regression of the standardized average daily consumption of online and offline markets on the year and before/after the Lunar New Year’s Day indicator,

$$Online_{jt} = \beta_{j0} + \beta_{j1} I(t > t^*) + \beta_{j2}year_{jt} + \beta_{j3}year_{jt} I(t > t^*) + \epsilon_{jt}$$  

where $t^*$ is the indicator for the Lunar New Year's Day. Thus, $\beta_{j3}$ indicates the impact of the intervention on online consumption that occurred in the year 2020. We model the offline consumption in the same way. The positive estimate indicates consumption increase due to the COVID-19 intervention, while a negative estimate indicates a consumption decrease due to the intervention. Then, the difference between the standardized average daily online and offline consumption for each category is contrasted,

$$\delta_{jt} = Online_{sdc_{jt}} - Offline_{sdc_{jt}}$$  

$$\delta_{jt} = \beta_{j0} + \beta_{j1} I(t > t^*) + \beta_{j2}year_{jt} + \beta_{j3}year_{jt} I(t > t^*) + \epsilon_{jt}$$  

The substitution effect can be reflected by $\beta_{j3}$, which measures the increase of online consumption compared to offline consumption, due to the COVID-19 intervention. If there is a positive substitution
effect from offline to online consumption due to COVID-19, $\delta_j$ is over 0. Otherwise, a negative substitution effect is expected.

4 | RESULTS

4.1 | Overall consumption change after the epidemic outbreak

The total consumption in the two periods (from December 28th 2019 to April 18th 2020 and from January 8th 2019 to April 30th 2019) was $3,347.08 and $3,038.71 billion, respectively. The amount of total consumption in 2020 fell by 9.2% compared to 2019 in the analyzed period. The standard value of 2020 was 14% higher than in 2019 because of increased consumption in the first week. The standardized average daily consumption before the intervention in 2019 was 1.088 and the indicator after the intervention was 1.022, a decrease of 7.9%. In contrast, the standardized average daily consumption after the intervention in 2020 saw a decline of 35%, with a drop from 1.105 to 0.718.

Although the total consumption in the Golden Week of 2019 embraced a boom compared to the other days in the year, it showed a decrease regarding the standardized value, which is compared with the benchmark, the average daily consumption of the first week.

We built the ARIMA models based on the standardized daily consumption in both years. The estimated coefficient and associated standard errors of the ARIMA models for standardized daily consumption in 2020 and 2019 are shown in Tables 1 and 2. The fitted and actual standardized daily consumption in 2020 and 2019 are presented in Figure 1.

As far as the standardized daily consumption is concerned (Figure 1), three features are apparent: First, both years’ individual consumption saw a peak in the week before the Lunar New Year’s Day. In contrast, transactions exhibited a big decline in the first week after the Lunar New Year’s Eve in both years. The last month before the Lunar New Year’s Day (or the 12th month in the lunar calendar) was the traditional consumption peak, which was consistent with our expectation. Second, the standardized daily consumption in 2020 was obviously lower after the intervention of the COVID-19 epidemic, but the daily consumption in 2019 went up steadily in 1 week. The holiday had its effect only in the first week immediately after the Lunar New Year’s Eve in 2019. The intervention of COVID-19 in 2020 was discernable compared to 2019. Third, consumption on weekends was generally lower than working days, which is known as the day-of-the-week effect.

We built the regression model based on the fitted standardized daily consumption in 2020 and 2019. For the regressed $d_t$ on the indicator of before or after the Lunar New Year’s Day, we obtained a regression coefficient $\hat{\beta}_1 = -0.2784$, with a $p$ value smaller than 0.001, which indicates that the decrease in standardized daily consumption in 2020 compared to that in 2019 is larger for the days after the Lunar New Year’s Day than before the Lunar New Year’s Day. The result verifies the negative effect of the COVID-19 outbreak in 2020.

### Table 1 Estimated coefficient and associated standard errors of ARIMA model for standardized daily consumption in 2020

| Parameters | $\phi_1$ | $\phi_2$ | $\phi_3$ | $\phi_4$ | $\phi_5$ |
|------------|----------|----------|----------|----------|----------|
| Estimate   | 0.1289   | -0.3156  | 0.0065   | -0.0844  | -0.3521  |
| S.E.       | 0.0894   | 0.0906   | 0.0954   | 0.0931   | 0.0932   |
4.2 The changes in online and offline consumption of different categories after the epidemic outbreak

Overall, the amount of online consumption in 2020 increased by 5.2%, whereas the amount of offline consumption decreased by 15.2% during our observation period. In addition, the share of online consumption in total consumption rose from 29.0% to 34.0%.

We regressed the standardized average daily online and offline consumption on the year and before/after the Lunar New Year's Day indicator for each consumption category. Table 3 shows the estimated average decrease of online and offline consumption in 2020 compared to 2019 after the Lunar New Year's Day due to the intervention. The positive estimate indicates a consumption increase due to COVID-19, while the negative estimate indicates a consumption decrease due to the virus.

The results in Table 3 imply that the intervention of COVID-19 had a substantial negative influence on the consumption of both channels. The regression coefficients show that both channels saw decreases

| Parameters   | \( \theta_1 \) | \( \theta_2 \) | \( \theta_3 \) | \( \theta_4 \) |
|--------------|----------------|----------------|----------------|----------------|
| Estimate     | 0.9119         | 0.7961         | 0.4605         | 0.4776         |
| S.E.         | 0.0783         | 0.1301         | 0.1529         | 0.1115         |

**FIGURE 1** Fitted and actual standardized daily consumption in 2019 and 2020
after the intervention compared to 2019. However, the effect varied among categories and channels. The offline consumption of four categories declined—tourism, health care, utilities, and education—whereas the online consumption of five categories dropped—tourism, utilities, traditional catering, financial services, and education. Tourism, utilities, and education decreased in both channels. The reduction in online consumption was lower than in offline consumption for tourism and utilities, whereas the online consumption of education saw a sharper decrease than the offline consumption. The online consumption of financial services and traditional catering dropped by more than 66%. Only online health care and online luxury rose, growing by 40.76% and 27.9% after the intervention, respectively.

It is easy to interpret the consumption reduction in tourism, utilities, and education for both channels. Due to the lockdown policy, people were not allowed to travel and tourist attractions stopped business. Furthermore, factories and office buildings were closed for more than 1 month. Utilities consumption was closely related to demand and the sales or payment channel would not stimulate demand if offices and factories were kept closed or were partly open. Therefore, electricity and water usage remained low. Education and training institutions were not allowed to open until May and they suffered the greatest loss among the three categories.

The increase in online health care indicated the soaring demand for both emerging online doctor visits and emergency medical supplies, such as face masks and medical gloves. Traditional catering and financial services dropped remarkably in the online channel as it is reasonable that few people dined out during the epidemic outbreak. Concerning online catering service, we assume that people were still worried about the food safety, while another reason might be that working from home saved commuting time and people could cook for themselves. The decrease in online financial services echoed the rising deposits in banks in the first quarter, because people were anxious about losing their jobs and the extra medical expenditure due to the epidemic. Finally, the stock market was also closed for several weeks, resulting in the decreased personal financial trading volume.

| Category              | Estimated (online) | Estimated (offline) |
|-----------------------|--------------------|---------------------|
| Transportation        | −11.36             | −17.55              |
| Tourism               | −17.08**           | −19.08*             |
| Retail                | −9.32              | 1.11                |
| Health care           | 40.76*             | −35.15**            |
| Luxury                | 27.90*             | −14.55              |
| Utility               | −24.78**           | −31.07*             |
| Traditional catering | −103.82***         | −10.11              |
| Commercial service    | 124.34             | −11.87              |
| Recreation            | 12.18              | −20.02              |
| Stationary            | 2.275              | −14.52              |
| Clothing and bags     | −3.88              | −4.34               |
| Financial service     | −66.31**           | −32.58              |
| Education             | −97.92**           | −76.15***           |
| Construction materials| 4.59               | −16.29              |
| Maternal and infant supplies | −3.6          | −12.73              |

*p < .1; **p < .05; ***p < .01.
4.3 The substitution effect between online and offline consumption after the epidemic outbreak

The results of $\delta_{jt}$, the differences between standardized average daily online consumption and offline consumption for category $j$ and week $t$, are shown in Figure 2. The blue dashed line rises from week 5 (dashed vertical line) compared to the solid red line if there is a positive substitution effect from offline to online consumption due to the intervention. However, a negative substitution effect from offline to online consumption due to the intervention is expected.

The estimated substitution effects from offline to online of the 15 categories are shown in Table 4. The categories fall into three groups.

The positive substitution effect from offline to the online channel after the epidemic outbreak was significant for the first group. The blue dashed line went up from week 5 compared to the solid red line in Figure 2. The standardized average daily online consumption of these categories after the intervention in 2020 increased faster than before the intervention compared to 2019. In contrast, their standardized average daily offline consumption noticeably declined after the intervention compared to 2019. Health care, luxury, recreation, and construction materials fell into this group.

When the offline market was impacted by the outbreak of the epidemic, it was possible for consumers to shift to the online market for these categories based on product characteristics. With construction material, for example, products could be displayed online and there were standardized specifications for most product models. The substitution elasticity from offline to online of health care was the highest among the 15 categories, implying not only the medical supply sales’ flexibility, but also the panic due to the epidemic.

A negative substitution effect from offline to online was discernible for the second group, although there was only one category in this group, which was traditional catering. The blue dashed line went down from week 5 compared to the solid red line. The standardized average daily offline consumption dropped more slowly than the standardized average daily online consumption after the intervention.

FIGURE 2 The standardized average daily online consumption and offline consumption
in 2020. The performance of traditional catering was the worst of all online markets, indicating that online ordering and food delivery services were not as desirable as picking up meals in restaurants.

The substitution effect from the offline to online channel was not significant for the third group, which was the largest, consisting of 10 categories. The blue dashed line and the solid red line intersected between week 5 and week 16. In other words, the substitution effect showed a great variation in different phases.

There were three sub-classes. The substitution effect from the offline to the online market was stronger in the first phase, but weaker in the second phase for clothing, stationery, utilities, and financial services. People shifted quickly to online shopping in the first phase, but they soon returned to the offline channel in the second phase, when the epidemic was almost under control. For instance, customers needed to try on clothing and shoes in stores, so they might prefer offline shopping when the epidemic was under control because it allowed them to examine products and gain instant gratification (Grewal et al., 2004).

In contrast, the substitution effect from the offline to the online market was weaker in the first phase but stronger in the second phase for sub-class two: maternal and infant supplies and education. People were unsure about the reopening date of education and training institutions, as well as early education organizations, until April. Therefore, both the online and offline markets dropped sharply in the first phase. People could only make online payments in the second phase since the institutions remained closed at that time, giving rise to a substitution effect from offline to online consumption.

The substitution elasticity fluctuated throughout the 12 weeks after the intervention for categories in the third sub-class: retail, tourism, transportation, and commercial services. They either swung between online and offline channels or decreased in consumption in both channels.
The results indicate that the COVID-19 outbreak and the following 40-day lockdown policy implemented across the country had a substantial impact on consumption. However, the effect varied among categories and market channels.

Overall, online consumption was more resilient than offline consumption. Two categories saw increases and five categories witnessed decreases in online consumption, whereas one-third of the categories dropped remarkably and none increased in offline consumption according to the regression analysis. The figures from the National Bureau of Statistics demonstrated that the total retail sales of consumer goods dropped by 15.8% and 7.8% in March and April compared to 2019, whereas online retail sales went down by 0.8% and increased by 4.5% (National Bureau of Statistics, 2020), which confirmed our findings.

The regression coefficients also showed that the substitution effects from the offline to online market after the COVID-19 intervention were significant for nearly one-third of the categories. It is worth noting that, despite the observed substitution effects after the intervention, the offline service could not meet the demand for some categories, such as health care. People rushed to purchase medical supplies in the online market to avoid going to crowded pharmacies. They could have treatment recommendations by calling doctors or visiting doctors online. However, medical examinations, surgeries, and hospitalization were all offline services. Citizens' offline health care demand was restrained rather than replaced by the online services.

Online consumption also played a similar role in recreation. Gyms, cinemas, spas, and bookstores were closed due to the lockdown policy. However, consumers could buy books online, watch movies online, and take online fitness courses and, thus, the online recreation market increased after the outbreak compared to 2019 and a substitution effect was discernible. However, spas and cultural performances were irreplaceable. Consumers did not have alternatives and the loss of offline consumption during this period was unrecoverable. These industries suffered some loss due to the offline service characteristics, although the online market demand grew.

The substitution effects of two-thirds of the categories were not significant, but they had different stories. Retail was closely related to citizens' daily lives. Most supermarkets and stores remained open after the intervention and people went shopping at a lower frequency but did not buy less, because they still needed necessities. In normal times, consumers also purchase online due to the convenience of online shopping and the online channel is an extension of the offline channel regarding grocery shopping (Chu et al., 2010). Consumers swung between the online and offline channels after the intervention and, therefore, the offline market for retail was least affected. Transportation and tourism also showed an insignificant substitution effect, but their online and offline markets both decreased significantly and they could not substitute across the markets due to low demand. Furthermore, related studies show that Chinese oil demand has fallen by 20% (Norouzi et al., 2020), whereas plastic processors worked at between 30% and 60% of their full potential (Norouzi et al., 2020). A similar trend arose in a Brazilian city after the COVID-19 outbreak, where water consumption decreased by between 30% and 53% (Kalbusch et al., 2020).

Some categories’ substitution elasticity showed different trends from the above categories and they changed in different phases after the intervention. The substitution effect was significant in one phase but was weak in other phases during the analyzed period, which depended on both public health control policies and customers’ psychology. Clothing and bags had the opposite trend to maternal and infant supplies and services, but they both showed an insignificant substitution effect.

The most vulnerable categories in a short period after the epidemic intervention were transportation, tourism, education, and traditional catering. Consumers made online payments for their plans...
in the near future. They might prepay or book tickets and services online. However, the end of the outbreak was not predictable in February and March and, thus, people were very cautious about future travels and studies. Schools were not open until late May in China. Education and training institutions and companies were not allowed to reopen offline classes until public schools were open, according to the lockdown policy, and parents hesitated to prepay for offline classes.

Both online and offline consumption dropped because of shrinking demand. Consumers worried about the health risk of online services, such as traditional catering because they were very sensitive to dietetic hygiene during the epidemic. According to the National Bureau of Statistics, traditional catering sales fell 46.8% and 31.1% in March and April, respectively, compared to 2019. This result was in accordance with the catering industry development trend in the U.S. after the intervention. In addition, freight turnover dropped 18.7%, 9.0%, and 4.1% and passenger turnover decreased 85.7%, 71.5%, and 65.3% in February, March, and April compared to 2019 (National Bureau of Statistics, 2020). Taking the passenger turnover and freight turnover, for example, they demonstrated the passenger and freight volumes transported, but the consumption of transportation included consumers’ reservations or payment in advance. Therefore, the reduction rates were different between the official statistics and our results.

Lastly, the current classification of companies needs to be adjusted. Some Information Technology (IT) companies registered their scope of business as e-commercial services and developed apps that provide a web platform for takeout catering services for customers and restaurants. However, the online consumption of restaurants and canteens were classified into traditional catering. In addition, some IT companies developed apps that provide a grocery shopping service. The effect of this was that consumers purchased daily necessities and takeout meals, but the consumptions were classified into commercial services, which was the market competition between traditional restaurants’ online service and emergent IT companies. In most cases, the latter distributed vouchers or coupons so that consumers paid less to buy the same meal from their apps than from the restaurants’ websites. The same was also true of grocery markets, supermarkets, and transportation.

There was a boom in the online consumption of commercial services after the intervention. Therefore, according to the business’s registered scope, the category of consumption should be subdivided into their actual business, especially e-commerce and IT companies as they play a third party role and might provide a wide scope of service that is different from the traditional classifications.

6 CONCLUSION

Thirty percent of the global population has been placed in lockdown and 80% of the workforce had their workplace closed due to COVID-19 (Norouzi et al., 2020; WHO, 2020). This paper has analyzed the COVID-19 intervention’s impact on individual consumption. The consumption changes for different channels and categories compared to 2019 were examined, with China as an empirical case. The substitution effects between the online and offline channels were also contrasted among different categories.

We draw three main conclusions from our models: First, generally, the COVID-19 epidemic’s intervention had a greater negative influence on offline expenditure. Second, there were substitution effects from the offline market to the online market for roughly one-third of the 15 categories. Furthermore, the offline services could not meet some categories’ demands due to the product characteristics. Lastly, the most vulnerable categories in a short period after the intervention were traditional catering, education, tourism, and transportation.
Jung and Sung (2017) investigated three consumption categories during the MERS outbreak in South Korea. We expanded the scope to 15 categories. The substitution effect of luxury and the relative stability of daily necessity consumption shown in our results was in accordance with their study. However, we detected more categories whose substitution effects after the COVID-19 epidemic were not significant.

Our results also echoed the statistics from the National Bureau of Statistics and relevant studies (discussed in Section 5). Despite similar change trends, we conducted more detailed analyses. First, the official website only showed monthly data, and the consumption was not subdivided into categories, and the weekly consumption change of different categories could not be detected. Second, the most indicators’ values in January and February were missing so the trends before and after the intervention between the 2 years could not be compared. Third, official data were collected from the current sales or service perspective, whereas our consumption data also reflected the reservations or expectations for the future. We discussed two problems in addition to the conclusions drawn from the regression coefficients. On the one hand, even if there was a substitution effect of online consumption, the offline service was not replaceable for a few categories due to the product characteristics. On the other hand, the substitution effect varied across different phases of the analyzed period, which is to say, it changed in a short period.

From a broader policy standpoint, three implications for policy on consumption promotion under extreme events emerge from our result. First, for categories whose substitute effects from the offline market to the online market are significant, the government is expected to adopt policies such as lower administrative barriers for these categories’ logistic systems after the outbreak to promote the substitute effect. Second, maintaining the stability of local public service is of great significance despite discernible substitution effects. Health care’s emergency resources should be optimized to maintain a basic healthcare service in extreme events. Third, vulnerable industries need more support from the government to prevent business failures. Traditional catering plays an important role in macroeconomy (National Restaurant Association, 2017). The subsidies, tax relief, and reemployment services for workers in traditional catering, education, tourism, and transportation should be put forward promptly after the outbreak. More than 80% of the small and medium enterprises have requested tax relief, whereas 60% have requested employment and operating subsidies (Lu et al., 2020). Last, but not least, cross-industry cooperation should be enhanced to promote the traditional industries’ recovery, for instance, IT companies providing a platform for catering companies.

Admittedly, this research has several limitations. First, the COVID-19 epidemic is still currently underway and we used a short-term data set, which spans only three and a half months around the intervention, preventing a study of its full impact to date. Therefore, it is not possible to identify the macroeconomy’s long-term trend. Second, we examined the consumption change on a national level with an overview of the national consumption market. However, the differences among regions are neglected. Third, we revealed the variations in consumption change and substitution effects among categories, but we did not explore the impacting factor and the consumption change mechanism of a specific category.

The above brings us to future research. We should carefully trace the changes in consumption over a longer period. In addition, an in-depth study of comparing the regions where the attack rate and mortality rate are different would be conducive to making targeted local policies. Finally, future research should discuss the determinants of the variations in a certain consumption category to provide implications for policies in extreme events.

**DATA AVAILABILITY STATEMENT**

The data that support the findings of this study are available from the corresponding author upon reasonable request.
ENDNOTES

1 Macroeconomic growth consists of three main elements: investment, export, and consumption.

2 The Lunar New Year’s Day is the first day after the Lunar New Year’s Eve. The Chinese New Year Golden Week starts from the Lunar New Year’s Eve to the sixth day of the Lunar New Year.

3 The Union Pay data set covers all the cities in China. To determine the share of Union Pay in total consumption, we sampled 31 cities: Shanghai, Beijing, Guangzhou, Shenzhen, Qingdao, Xiamen, Hefei and all the cities in Jiangsu province and Zhejiang province.

4 Consumers’ personal bank cards can be bound with their Alipay and Wechat Pay (the same as PayPal) account.

5 http://www.gov.cn/xinwen/2019-04/17/content_5383727.htm.

6 Consumption on weekends is generally lower than on weekdays.

7 Employment in the restaurant industry had grown from 11.9 million in 2004 to 14.7 million in 2017, which comprises 10% of the overall U.S. workforce.

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## APPENDIX

**Consumption categories**

| Category                  | Merchants                                                                                                                                 |
|---------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| 1  Traditional catering  | Fast food restaurant, Canteen in hotels, Regular restaurant, Pub, Night club, Café, Bakery, Bucher's shop, Dairy shop, Sweet shop, Banquet, contractor, Snack shop, and Liquor shop |
| 2  Clothing and bags      | Clothing store for women, men, and kids, Naturel Leather Shop, Shoe shop, Bag shop, Draperoy shop, Sportswear shop, Accessory shop, and Uniform wholesaler |
| 3  Stationary and digital devices | Software shop, Electronic device shop, Mobile phone shop, Stationary shop, Electric parts shop, Office furniture shop, and Office equipment shop |
| 4  Construction material  | Household appliance and equipment shop, Furniture shop, Flower shop, Glassware and paint, Hardware store, Floor store, Curtain shop, Interior remodeling, Construction material wholesale, Home decoration store, and Pipe and heating equipment shop |
| 5  Recreation and sports  | Book shop, Audio and video product shop, Handicraft shop, Photo equipment shop, Gambling and lottery, Video game shop, Cinema, Campsites, KTV, Bowling alley, Swimming pool, Stadium, Sports club, Golf course, Fitness club, Playground, Performance and show, Amusement park and carnival, Aquarium, and Beauty SPA |
| 6  Tourism and accommodation | Recreational vehicles and campsites, Travel agency, Accommodation and resort, Exhibition, and Tourist attraction ticketing |
| 7  Financial service      | Insurance, Credit card repayment, Securities, Manual and cash payment to financial institutions, Pawn, and auction and trust                  |
| 8  Transportation        | Taxi, Regional coach, Airport service, Railway ticketing, Airline company, Steamer ticketing, Charter ship, Toll fee, National postal service, Express service, Tobacco logistics, Petrol logistics, Gas station, Auto parts shop, Tire shop, Motorcycle parts, Automobile, aircraft and agricultural machinery, Truck dealer, RV sales, Snowmobile, Motorcycle dealer, Garage, Car wash, Vehicle towing, Car rental, RV rental, Truck and trailer rental, and Automobile association |
| 9  Health care           | Pharmacy, Dentist, Public hospitals, Vet, Ambulance, Oculist and optometrist, Massage, Nursing, and Orthopedic Hospital                         |
| 10 Education             | Primary and middle schools, Colleges and universities, Remote education, Business and technique training, and Private education services         |
| 11 Luxury                | Precious jewelry and watches, Antique reproduction, Silverware, Glassware and crystal, and Optical instrument and products                     |
| 12 Commercial service    | Information retrieval, Photographing, Printing and photocopying, Detective and security service, Legal service, Landscaping, Audit, Storage service, Tax consulting, and Private affair consulting |
| Category                              | Merchants                                                                 |
|---------------------------------------|---------------------------------------------------------------------------|
| 13 Utility and public service         | Telecommunications service, Utility service, Tax payment, Court cost, Bail, Embassy service, Other government service, Fine, and NGO |
| 14 Retail                             | Cosmetics shop, Prosthetics shop, Wig shop, Telesales, Second-hand shop, Catalog sales, Subscription sales, Wholesale supermarket, Grocery and convenience store, Household store, Duty-free shop, and Discount shop |
| 15 Maternal and infant supplies and services | Child care, Maternal care, Baby care, Toy store, Ladies’ goods store, and Baby supply store |

Results of standardized consumption before and after the lockdown policy

| Category                              | Time | 2020 online | 2019 online | 2020 offline | 2019 offline |
|---------------------------------------|------|-------------|-------------|--------------|--------------|
| Transportation                        | Before | 0.80 | 0.95 | 0.98 | 0.99 |
|                                       | After  | 0.39 | 0.64 | 0.65 | 0.84 |
| Tourism                              | Before | 0.92 | 0.93 | 0.96 | 1.09 |
|                                       | After  | 0.50 | 0.67 | 0.79 | 1.11 |
| Retail                               | Before | 0.95 | 1.01 | 0.98 | 1.11 |
|                                       | After  | 0.82 | 0.97 | 0.77 | 0.90 |
| Health care                          | Before | 1.00 | 1.08 | 0.92 | 0.96 |
|                                       | After  | 1.18 | 0.85 | 0.60 | 0.94 |
| Luxury                               | Before | 0.97 | 0.94 | 0.96 | 1.16 |
|                                       | After  | 1.29 | 0.98 | 0.76 | 1.10 |
| Utility                              | Before | 1.05 | 1.09 | 0.89 | 0.89 |
|                                       | After  | 0.80 | 1.08 | 0.31 | 0.61 |
| Traditional catering                 | Before | 1.21 | 1.31 | 0.97 | 1.11 |
|                                       | After  | 0.36 | 1.50 | 0.74 | 0.98 |
| Commercial Service                   | Before | 1.49 | 0.99 | 1.00 | 1.09 |
|                                       | After  | 2.97 | 1.23 | 0.73 | 0.94 |
| Recreation                           | Before | 0.96 | 0.96 | 0.94 | 1.09 |
|                                       | After  | 1.14 | 1.02 | 0.77 | 1.12 |
| Stationary                           | Before | 0.94 | 0.99 | 1.03 | 1.10 |
|                                       | After  | 0.89 | 0.92 | 0.69 | 0.91 |
| Clothing and bags                    | Before | 1.02 | 0.99 | 0.99 | 1.05 |
|                                       | After  | 0.99 | 1.00 | 0.57 | 0.67 |
| Finance                              | Before | 1.46 | 1.09 | 1.40 | 1.27 |
|                                       | After  | 1.10 | 1.40 | 0.58 | 0.78 |
| Education                            | Before | 0.87 | 1.13 | 0.91 | 0.97 |
|                                       | After  | 0.56 | 1.80 | 0.32 | 1.14 |
| Construction materials               | Before | 1.06 | 0.99 | 1.01 | 1.07 |
|                                       | After  | 1.04 | 0.92 | 0.75 | 0.97 |
| Maternal and infant supplies and services | Before | 0.81 | 0.98 | 0.96 | 1.15 |
|                                       | After  | 0.67 | 0.87 | 0.74 | 1.05 |