Online Consumption during Long-term and Normalized COVID-19 Pandemic

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Abstract. COVID-19 has attacked consumers' demands and investors' confidence in purchasing stocks. This paper studies the impacts of COVID-19 on both China and overseas online shopping. Two models including a VAR and an ARMA-GARCHX model are built in this research. Respectively, the VAR model is utilized to analyze how newly confirmed pandemic cases influence the logarithm of online consumption yield rates, while the GARCHX model is used to study how the pandemic affects the volatility of online shopping. This paper finds that Coronavirus has a subtle effect on online consumption in China in the long term, while a more obvious shock on that overseas. The finding can also become a meaningful inspiration for policymakers and investors. On a national level, Chinese government ought to encourage the development of digital economy and support the online transformation of traditional offline firms. Moreover, the financial investment to improve the logistics system is a necessity. Properly subsidizing low-income groups is also fundamental to maintaining people's demands and confidence. On a personal level, investors should invest in companies with high financial liquidity and competence in digital innovation like e-commerce companies and online office software. All these fields accord with people's less time away and more time at home.

Keywords: COVID-19; Online consumption; newly confirmed cases.

1. Introduction

The COVID-19 pandemic, the knottiest crisis in recent years, has left severely negative impacts on the global economy. Normal employment, production, trade, and a variety of economic activities have been attacked. In order to prevent the virus from continuously spreading, Chinese government has been implementing the containment and lockdown policy. People are required to isolate themselves at home to avoid being infected when contacting others, controlling the frequency and time of going out. Restricted by the mandatory stay-at-home quarantine, most people have no way of entertainment but to increase their dependence on social media [1]. With more time spent on the Internet, consequently, people have transformed to adapt to the online channel to purchase daily products that they are unable to access offline. The change in consumers' behaviors subsequently led to the growth of e-commerce, accelerating the marketing innovation and digital transformation of firms [2, 3].

This section will recapitulate some previous work, with all either directly or indirectly functioning as effective references for this paper. It will start with works focusing on Chinese people's social media use during the pandemic, illustrating the change in Internet usage frequency since the pandemic. Then it will cover all possible factors that affect consumers' online shopping during the Coronavirus. Additionally, it will contain some general strategies used by firms to resist either a natural or artificial disaster. Besides, it will include the development of e-commerce and the online transformation of Chinese companies in COVID-19. Last but not least, except for the development opportunities brought by the containment policy to online commerce, it will also cover some difficulties.

Luo, Chen, and Liao studied people's use of social media during COVID-19 [1]. By comparing the social media use patterns before and during the pandemic, they found that there was a fundamental increase in the time used on social media and the prevalence rate of social media addiction was high. Meanwhile, they pointed out the correlation between emotions and dependence on social media. Specifically, the pandemic exacerbated many people's stress, anxiety, and depression, and the greater people's exposure to these negative emotions, the more dependent they are on social media.

Yan et al. studied the key factors that affect online consumption in the pandemic [4]. They found that major factors that impact online shopping under the normal social background did not play a role in this special period. Instead, new elements including people's opinions on COVID-19, low-efficiency logistics, the sluggishness of offline channels, official pandemic information, and the panic feelings brought by the pandemic become the most important causes. Moreover, taking Alibaba as an instance, Han and his peers focused on the e-commerce operation during the Coronavirus [2]. They stated that digital resilience and logistics capacity were two key operational drivers that impacted e-commerce sales. People who were not accustomed to shopping online in the past changed to adopt the online channel and made great contributions during the COVID-19, and this newly formed shopping behavior was likely to continue in the future. Similarly, by looking into the socio-economic cost of the pandemic on Chinese people's living patterns, Yuan et al. also agreed that people tended to adopt the life habits that were newly cultivated during the COVID-19 [5]. However, a restriction on offline mobility would hamper the delivery of packages purchased from online stores.

Naidoo emphasized the importance of marketing innovations for a firm when encountering a devastating crisis [6]. Based on his idea, Wang and other co-authors 2020 suggested that marketing innovation was a useful tactic for the survival of Chinese offline businesses during COVID-19 [3]. By utilizing the responsive strategy, these firms made good use of social media platforms, successfully transferring to the online sale model and catching consumers. Alfonso et al. in 2021 also drew a similar conclusion that the Coronavirus encouraged traditional companies to create new products and services like live streaming and virtual shopping [7]. Fundamentally, as measured by WIPO Global Innovation Index, a positive correlation between e-commerce to GDP and the innovation ability of an economy was shown. Synthetically, the digital innovation of conventional offline firms in China benefitted the national economy in COVID-19.

From a macro perspective, Bhatti and his colleagues in their paper studied the overall development tendency of e-commerce during the pandemic [8]. They concluded that COVID-19, in general, gave rise to the rapid growth of e-commerce not only in China but also around the globe. Specifically, they also pointed out that the impact of COVID-19 on some products was high, while its effect on other objects was relatively low. An obvious reflection of people's increasing reliance on e-commerce can be seen in the study of Yue et al. in 2021 [9]. Researching people's WTP on food during the pandemic, proved that there was an increase in people's online food consumption. Similarly, the study conducted by Gao et al. also led to the conclusion that the share of consumers' online food expenditure rose [10]. Especially young people in large cities, they were more likely to purchase food online.

Using the combination of ECM and TTF model, Al-Hattami 2021 did research on what determined people's continuous intention to purchase online under COVID-19 [11]. Based on the premise that the pandemic was expected to permanently normalize the usage of online consumption, he found that confirmation, perceived usefulness, and trust positively affected people's satisfaction towards the continuous utilizing the online shopping, and consequently, people's high satisfaction led to their intention of using online channels continuously.

Though COVID-19 makes people rely more on social media, providing an exceptional chance for the growth of e-commerce and online consumption, it is necessary to see the obstacles. First, the containment regulation and the shutdown of offline companies formed asymmetric business information. Consumers could rarely grasp accurate and complete information about resources and suppliers. Taking advantage of this asymmetry, many suppliers deliberately bid up and created panic. In the end, buyers had no alternative but to accept the extravagant price. Also, people with a lower income were hard to benefit from online shopping because they could not afford the increasing prices caused by the limited resources and lockdown policy [9]. Meanwhile, the government's excessive restriction on the delivery system results in low logistics capacity, which lengths the time of receiving goods and makes people unable to gain those necessities on time.

All these previous studies mainly concentrate on the market economy exactly in the initial stage when the Coronavirus was considered severe, and there is nearly no work aiming at the trend of online economy in China when the pandemic becomes normalized and relatively stable. Based on this situation, this paper explores the situation of online consumption in China and overseas in the interim and later period.

The following parts of this paper are organized as followings: Part 2 is the research design which includes data source, unit root test, VAR model specification, and ARMA-GARCHX model specification; Part 3 is empirical results of the research, covering VAR model results, ARMA-GARCHX model results; Part 4 is the discussion which contains the uniqueness of this paper and its guidance for the government and investors; Part 6 is the conclusion.

2. Research Design

2.1 Data Sources

Data in this paper can be categorized into two main parts. The first part is the data of newly confirmed pandemic cases in both China and the world, and they are derived from WHO. Another part of data is the logarithm of online consumption yield rates, and they are calculated by referring to the closing prices of stocks during the pandemic period from the PC Application Choice. As a professional financial data analysis and investment management software, PC Application Choice provides high-quality financial data and application tools such as Excel plug-in, quantitative interface, and portfolio management, which integrates information query, statistical analysis, and application [12].

2.2 Unit Root Test

A Unit Root Test (Process) tests whether a time series variable is stationary. Many time series are based on the prerequisite that the time series variable is stationary. In that case, the stationary condition of data must be checked before starting the research. If any time series variable is found to be non-stationary, this paper needs to provide some effective approaches to improve the results.

When it comes to the Unit Root Test, the time series variable is usually assumed to be written as:

$$\text{mt}= c_t + \beta m_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta m_{t-1} + \varepsilon_t \tag{1}$$

The null hypothesis of the test is that the coefficient $\beta = 1$. This means that there is a unit root and the series variable is not stationary. On contrary, the alternative hypothesis refers to that $\beta < 1$, which indicates that the series variable is stationary.

Table 1 provides the test outcomes of both the original data and the processed series.

Table 1. ADF test

0	t-statistic	p-value
Index		
Online consumption	-2.3620	0.4001
Yield		
Online Consumption	-12.3740	0.0000***
Covid-19 pandemic, newly confirmed cases		
Overseas	-6.8280	0.0000***
China	-4.0930	0.0064***

Note: ***, ** and * indicate the level of significance of 1%, 5%, and 10% respectively.

All the data here are results when the logarithm series of the original data has been taken. It can be found from the outcome that most of the logarithm series, except for the index variable online consumption, perform well in the stationary test. The yield variable online consumption, the newly confirmed cases in China, and overseas series are all significantly stationary under 99% confidence intervals. Based on the results, this paper could build the following models with these stationary series.

2.3 Vector-autoregression Specification

First formally put forward by Sims in 1980, Vector Autoregression (VAR) is a multivariate forecasting algorithm that is used when two or more two time series influence each other [13].

To clarify, suppose to measure a VAR model with three different time series variables c1, c2, and c3, and only one lag term (p=1). The system will be like this:

$$\begin{cases} c_{1,t} = \alpha_{11,1}c_{1,t-1} + \alpha_{12,1}c_{2,t-1} + \alpha_{13,1}c_{3,t-1} + \epsilon_{1,t} \\ c_{2,t} = \alpha_{21,1}c_{1,t-1} + \alpha_{22,1}c_{2,t-1} + \alpha_{23,1}c_{3,t-1} + \epsilon_{2,t} \\ c_{3,t} = \alpha_{31,1}c_{1,t-1} + \alpha_{32,1}c_{2,t-1} + \alpha_{33,1}c_{3,t-1} + \epsilon_{3,t} \end{cases} \tag{2}$$

Here the VAR model can be integrated into a vector group like:

$$C_t = \alpha \cdot C_{Lag} + E_t \tag{3}$$

where $C_t = \begin{bmatrix} c_{1,t} \\ c_{2,t} \\ c_{3,t} \end{bmatrix}, \alpha = \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} & \alpha_{13,1} \\ \alpha_{21,1} & \alpha_{22,1} & \alpha_{23,1} \\ \alpha_{31,1} & \alpha_{32,1} & \alpha_{33,1} \end{bmatrix}, C_{Lag} = \begin{bmatrix} c_{1,t-1} \\ c_{2,t-1} \\ c_{3,t-1} \end{bmatrix}, E = \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{bmatrix}$.

In this case with three variables (online consumption, overseas cases, China cases), a VAR(p) model should be written as:

$$z_t = \Gamma_0 + \Gamma_1 z_{t-1} + \cdots + \Gamma_p z_{t-p} + \mathcal{E}_t \tag{4}$$

where $z_t = \begin{bmatrix} z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix}, \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}, \Gamma_1 = \begin{bmatrix} \beta_{11} & \gamma_{11} & \lambda_{11} \\ \beta_{21} & \gamma_{21} & \lambda_{21} \\ \beta_{31} & \gamma_{31} & \lambda_{31} \end{bmatrix}, \dots, \Gamma_p = \begin{bmatrix} \beta_{1p} & \gamma_{1p} & \lambda_{1p} \\ \beta_{2p} & \gamma_{2p} & \lambda_{2p} \\ \beta_{3p} & \gamma_{3p} & \lambda_{3p} \end{bmatrix}$.

Here z_t represents the three response variables. $\Gamma_0, \Gamma_1, \dots, \Gamma_p$ refer to the coefficient matrix for corresponding terms. ε_t is the error term matrix in the period t.

In this case, the estimates of VAR are so many that are hard to analyze, and impulse response graph is a reliable choice that can be used to measure the interaction within a variable or between distinctive variables in the VAR system. Thus, a response graph generates an impulse exogenously and reflects how the system replies to it. Under normal conditions, the response effect is usually expressed as:

$$\psi_s = \frac{\partial z_{t+s}}{\partial \mathcal{E}_t} \tag{5}$$

From this equation, the response effect can be interpreted as the effect on the value of $z_{i,t+s}$ (the value of variable i in the timestamp of $t+s$) when there is one-unit increase of variable j in the disturbance term ε_{jt} at the timestamp t. It will become the Impulsive Response Function (IRF) if treating $\frac{\partial z_{i,t+s}}{\partial \varepsilon_{jt}}$ as a function with a time interval of s.

In a VAR model, one clear way to visualize the interaction within or between the variables is to draw a graph. Importantly, all of the impulsive responses within a VAR system can be drawn as graphs, and these graphs become fundamental evidence when analyzing the VAR model.

2.4 ARMA-GARCHX Specification

Considering that ARCH model takes the volatility of variance into account, it can better make the variance forecast. In that case, ARCH models are widely utilized in modeling financial time series which show time-varying volatility and volatility clustering [14]. Generally, an ARCH(p) model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \psi_s = \frac{\partial z_{t+s}}{\partial \varepsilon_t} \tag{6}$$

where σ_t refers to the forecast variance in the period of t, while ε_t is the actual variance in the period of t. α_0 is constant.

Put forward by Bollerslev in 1986, GARCH model essentially is an extension of ARCH model and supports a more flexible lag structure [15]. It decreases the number of parameters to be estimated, which allows for a more accurate prediction for the future condition variance. To elaborate, a GARCH (1,1) with three terms can be written as:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \psi_s = \frac{\partial z_{t+s}}{\partial \varepsilon_t} \tag{7}$$

If continuously putting GARCH equation for σ_{t-1}^2, σ_{t-2}^2, … into the equation, the function can be presented as:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-2}^2 + \cdots + \beta_p \varepsilon_{t-p}^2 + \cdots \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \psi_s = \frac{\partial z_{t+s}}{\partial \varepsilon_t} \tag{8}$$

which refers to an ARCH (∞) model with infinite terms.

More generally, a GARCH (p, q) model can be written as:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \cdots + \beta_p \varepsilon_{t-p}^2 + \gamma_1 \sigma_{t-1}^2 + \cdots + \gamma_p \sigma_{t-q}^2 \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \psi_s = \frac{\partial z_{t+s}}{\partial \varepsilon_t} \tag{9}$$

As one of the most fundamental factors, participants have to consider risks when engaging in the market economy. Also, people's gains from the market are usually positively correlated with the risks they are going to suffer. In that case, an ARMA-GARCHX model is an appropriate selection to assess the volatility or risk of stock prices. An ARMA-GARCHX model consists of two parts of value and variance, but the GARCHX part should be the focus when trying to understand the market risk.

3. Empirical Analysis

3.1 VAR Identification

In this part, three stationary series including logarithm online consumption, and logarithm newly increased confirmed cases in China and overseas are put into the VAR system. In the beginning, in order to get the appropriate order p of the VAR(p) model, different VARSOC selection-order criteria in Stata are utilized. The result listed in Table 2 suggests that 11 orders are contained in this VAR model.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-496.8140				0.0053	3.2775	3.2921	3.3141
1	-144.2280	705.1700	9	0.0000	0.0006	1.0245	1.0830	1.1709
2	-120.6970	47.0620	9	0.0000	0.0005	0.9292	1.0316	1.1853
3	-112.5050	16.3850	9	0.0590	0.0005	0.9345	1.0808	1.3004
4	-108.9990	7.0107	9	0.6360	0.0005	0.9705	1.1608	1.4462
5	64.6032	347.2100	9	0.0000	0.0002	-0.1089	0.1253	0.4766
6	66.1153	3.0242	9	0.9630	0.0002	-0.0598	0.2183	0.6355
7	72.9672	13.7040	9	0.1330	0.0002	-0.0457	0.2763	0.7594
8	77.9034	9.8724	9	0.3610	0.0002	-0.0190	0.3469	0.8958
9	79.1493	2.4918	9	0.9810	0.0002	0.0318	0.4416	1.0564
10	83.4108	8.5229	9	0.4820	0.0002	0.0629	0.5166	1.1973
11	84.6080	2.3945	9	0.9840	0.0002	0.1140	0.6117	1.3582
12	86.5831	3.9502	9	0.9150	0.0002	0.1601	0.7017	1.5141

After building VAR model and estimating the parameters of a vector autoregression, this paper checks the eigenvalue stability condition via Stata. By illustrating a unit circle, visualizes the result. When judging the stability, if all the plots which interpret the eigenvalues locate within the unit circle, it can be concluded that the VAR system satisfies the stability condition. Figure 1 shows the distribution of all the plots, which indicates that the VAR estimates are stable.

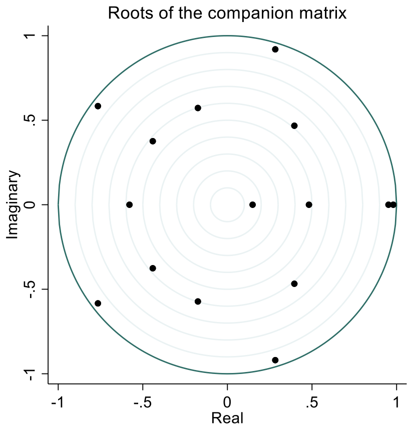

Figure 1. VAR stability

3.2 Impulse Response Graph

Figure 3 illustrates the impulse response results of variables of both new cases in China and overseas. Based on the impulse response function derived from the VAR model in this paper, it can be found that when the Coronavirus tends to normalize, domestic pandemic in China shows little impact on online consumption, with the net effect equaling 0. Similarly, the number of newly confirmed cases overseas increases by 1% in the period of t=0, and the online consumption index will fluctuate around the 0 value with a range of approximately 0.05% in the short term in the future, which is also a small in value. However, what is different is that the net effect left by the pandemic overseas on online consumption is negative. This might attribute to the decrease in the export demand. In terms of the time effect, current shocks will decay over time.

China Overseas

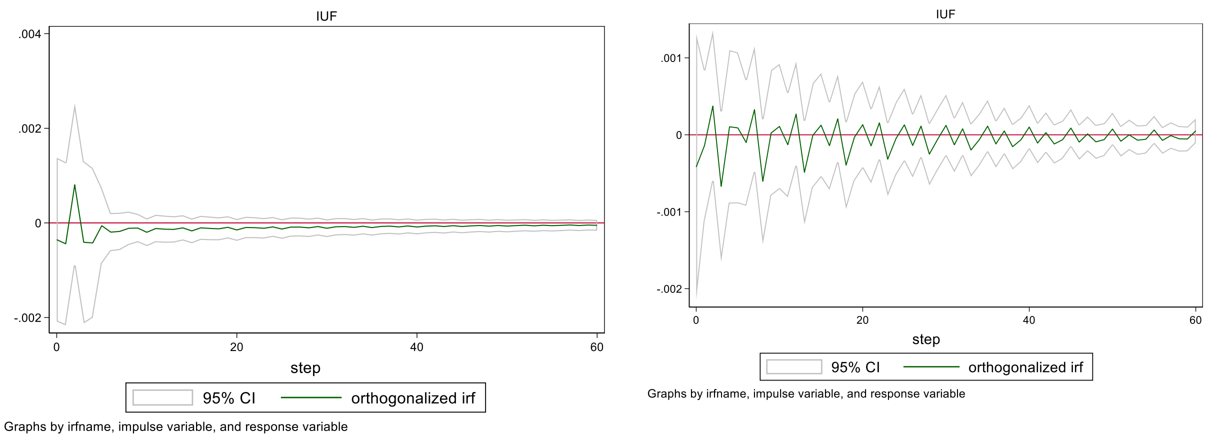

Figure 2. Impulse and response

3.3 Forecast

According to the VAR model outcome, this paper predicts the online consumption yields in the nearby future, and the outcome is illustrated in Figure 2. From the estimation results of the model, the yields of the online consumption industry will first show a downward tendency in the short term, and then gradually fluctuate and level off.

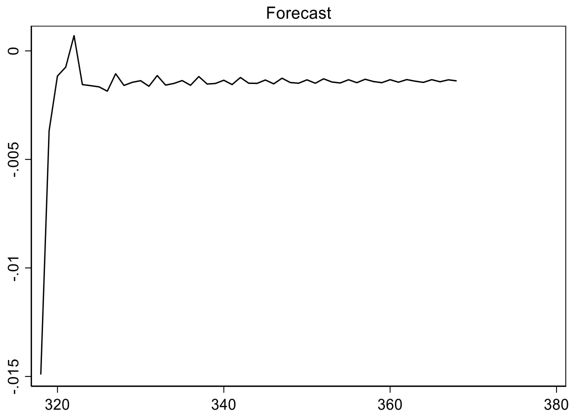

Figure 3. Prediction

3.4 Section Headings

In order to construct an ARMA-GARCHX model, both AR and MA parts of the logarithm of online consumption yield rate are firstly revealed in this paper.

Examine the partial autocorrelation plot (PACF plot) of the series, and the graph is displayed on the left side of Figure 4. Utilizing the rectangle to determine the statistically significant term in the AR model, it is found that the lag 4 terms might significantly influence the current data.

In addition, the paper determines the MA part of the series with the help of Autocorrelation Plot (ACF Plot), and the graph made by Stata can be seen on the right side of Figure 4. It reveals that the lag 4 term is a good selection.

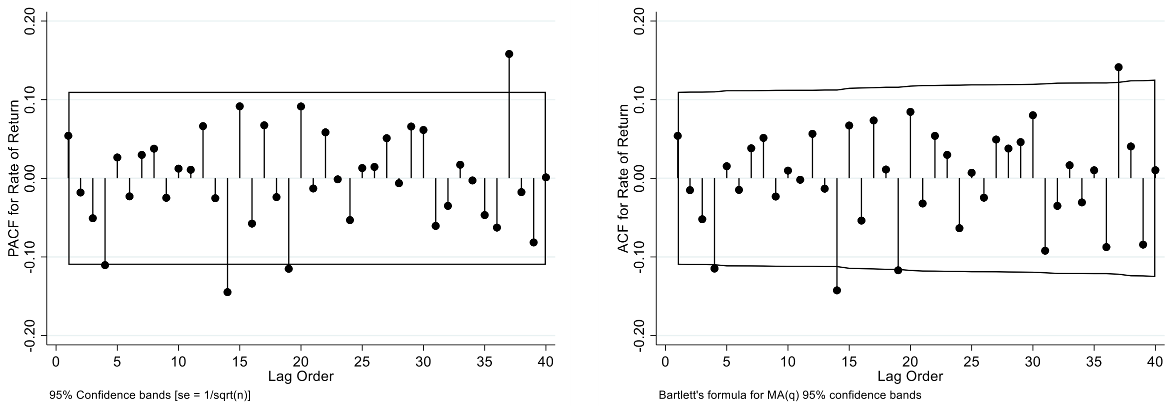

Figure 4. PACF and ACF

After determining both AR and MA parts, the paper builds the ARMA-GARCHX model. According to the ARMA-GARCHX estimation results in Table 3, the GARCHX term of the model in curriculum (1) is significant. Meanwhile, both the ARCH term and GARCHX term in curriculum (2) are significant. All of these indicate that the logarithm return series of online consumption index has statistically significant conditional heteroskedastic properties, thus the GARCHX modeling can be conducted.

Judging from the estimated coefficient of newly confirmed cases, the number of newly confirmed cases in China increases by 1%, and the volatility of the online consumption index return will correspondingly increase by 0.3585 units. Additionally, as the number of newly confirmed cases overseas increases by 1%, the volatility of online consumption industry revenue will show an increase of 0.4894 units. Therefore, the coefficient of the latter one is larger, which is probably due to the number of overseas cases being relatively large compared with that of China.

A GARCHX term can be put into use only when conditional heteroscedasticity is satisfied in the original sequence. Consequently, it is necessary to check the variance condition of the online consumption series before constructing an ARMA-GARCHX model. From previous results, it can be said that online consumption has conditional heteroscedasticity.

Table 3. ARMA-GARCH estimation results, variance equation

Variables	(1)		(2)	
	Coefficient	Standard error	Coefficient	Standard error
		New confirmed cases		
China	0.3585***	0.0618		
Overseas			0.4894***	0.1821
ARCH (-1)	0.0758	0.0544	0.1698***	0.0566*
GARCH (-1)	0.4627*	0.2518	0.5873***	0.1157
Constant	-10.7913***	0.7041	-16.3007***	2.6144

4. Discussion

This paper differs from former research conducted by other researchers in the conduction of three main parts. First, it concentrates on the general picture of online shopping in the long term when the pandemic tends to be normal. Second, it takes advantage of the stock closing prices to measure the online consumption yield rates during COVID-19. Last, it builds up the VAR and ARMA-GARCHX model with the assistance of Stata. Besides, instead of paying too much attention to the decline of online consumption when the Coronavirus is fierce, this paper makes distinctive discoveries by claiming that COVID-19, in general, has little impact on online shopping in China. Based on the discoveries, this study inspires that COVID-19 indirectly provides an opportunity for the development of e-commerce and digital economy in China. In that case, policymakers and officials in Chinese government have to catch this chance to facilitate the long-term growth of online economy. The government needs to properly publish some open policies, improve the transportation system, and accelerate the efficiency of logistics. What's more, Chinese government has to positively push employment and moderately increase wages. Also, decision-makers have to provide subsidies for both traditional companies which innovate to explore the online channel, giving financial support to people who have low income and are unable to afford many things. These measures can stabilize the confidence in economy and improve the desire to purchase things online. Moreover, this paper can enlighten investors' behaviors. Considering this unprecedented development chance for online firms, investors need to adjust for the sake of gaining. They can invest in stocks of companies that have some of the following features: have a great potential to make innovations and transform to online channels, be responsible for offering daily necessities, own a high delivery efficiency, and possess abundant capital and labor sources.

5. Conclusion

Coronavirus has brought both destructive and revolutionary effects on the global market economy. During this resistance process, people change their behaviors and adjust to making transactions online. At the same time, traditional offline firms actively engage in marketing innovation and develop e-commerce through online channels. In this context, this paper studies how newly confirmed cases in

China and overseas influence online consumption. Focusing on the logarithm of online consumption yield rates, this paper also researches its volatility response. Through the research, this paper finds out that in the short term after the outbreak of the pandemic, an increase of newly confirmed cases in China results in a dramatic decrease in people's spending online. However, with time going by, the damage caused by COVID-19 gradually declines and levels off. Overall, in the long term, the aggravation of the pandemic has a subtle impact on online consumption in China. Compared with that of China, the shocks brought by the pandemic are relatively fierce, and this probably results from a larger base of overseas population.

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