Entertainment Industry under Normalized Covid-19 Pandemic: An Empirical Evidence Based on Time-series Model

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Abstract. In January 2020, the coronavirus, known as COVID-19 launched the first strike in Wuhan China, shutting down the local economy and causing massive loss. The expeditious spread of COVID-19 then became a global epidemic. The ubiquitous virus is jeopardizing both home life and economical life. The main objective of this paper is to examine how tourism, catering, and hotel stock returns respond to the stress of the Covid-19 pandemic in Chinese market. Secondary data of 3 collective stocks as well as pandemic data for China and overseas have been collected from Choice.eastmoney.com and WHO website from 23rd January 2020 to 21st January 2021. This paper employs an ARMA model, a VAR model, and an ARMA-GARCH model for analyzing changes in market returns and volatility. This paper finds adverse effects of domestic pandemic on the three markets, with hospitality being the least affected one. Neither global nor Chinese newly confirmed cases significantly influence volatility in observed industries. The results are appliable for investors and policymakers.

Keywords: Covid-19; Rate of return; Volatility; Entertainment.

1. Introduction

Contagious diseases like COVID-19 are damaging every aspect of lives. People are facing unemployment during lockdown, infant firms are dying without investments, and unpredictable pandemic is psychologically challenging everyone. By 27 January 2021, world total confirmed cases passed over 100 million in 207 countries. The impact of COVID-19 on tourism and related sectors resulted in over $4 trillion blow to world economy by end of 2021 [1]. Literature suggests a strong relationship between market returns and infectious diseases like Ebola, SARS, and COVID-19 [2-6]. Severe pandemic will inevitably undermine consumer confidence thus shrinking consumption world widely, and consequently, affecting production and service industry as well as investment [7].

More recent studies specifically explore coronavirus and financial market dynamics attract great academic attention. In Ahmad Bash' s research, significantly negative reactions are detected in market returns by analyzing 30 stock indices across world [8]. In more detailed research that summarizes over continents, Rehan, M. and collogues conduct research regarding 41 stock exchange volatilities across 32 countries under short-term stress of COVID-19 [9]. EGRCH model from ARCH family models is employed to deal with asymmetry volatility. This research not only advocates a significant negative relationship between the number of new COVID-19 cases and stock indices but also suggests an increasing clustering effect with the rapid increase of COVID-19 cases. More importantly, Rehan claims in research that Asian stock markets have the least volatility against confirmed cases. Arguably, this research focuses more on the initial stage of the pandemic (till May 2020) and makes comparison to the normal stage (from June 2019). How stock volatility varies in the longer term is less well-explained. Focusing on Asian areas, where pandemic began and interestingly, was least affected at the same time, more studies bring good insights. Alali, M suggests pandemic outbreaks have long-term impacts on Chinses stock market [10]. A paper from Gil-Alana reinforces Alali's statement by proving long-lasting stock shocks drawn onto the Asian market [11]. However, two searches only elaborate on the nature of the COVID-19 shock on markets in a time series. Datasets included are ended by the third quarter in 2020, limiting results to reveal market return fluctuations when the market gradually adapts to the pandemic shock. More surprisingly, equity markets begin to rebound when the pandemic carries on. After the initial shock, market returns seeking the chance to recover once the diseases become less severe than expected [12]. Therefore, market performances may vary during the later stage of the pandemic. This paper will then extend the analysis to demonstrate after the epidemic begins, within a longer term, how stock volatility varies with pandemic severeness.

Among two kinds of pandemic descriptive data, daily confirmed and death cases, conflicts would arise when researchers aim to utilize the more related one to stock indices. Nicholas, A. and collogues build a GARCHX model to investigate the rate of return changes in Chinese market against deaths and confirmed cases, respectively. Results document that impacts of the Covid-19 on stock returns are more pronounced when total deaths included in the model [13]. The second strand of literature address how financial markets respond to newly confirmed stats. Bardar, A. provides a simple panel data regression to analyze how stock market returns behave differently when impacts of COVID-19 represented by confirmed cases and deaths. The result documents stock market reacted more proactively when a daily confirmed proxy of this infectious disease, and the response varies over the stage of the outbreaks [14]. Similarly, Nur, M. and Noraini, N uses panel regression and discovers a coefficient of -0.172 stock market decreasing when every confirmed case increased. The coefficient of market returns against pandemic deaths is -0.066, proving confirmed cases as a more proactively variable [15]. Arguably, three research utilize different pandemic data sets. Nicholas employs Chinese COVID-19 stats and Nur and collogues use local Malaysian data sets while Bardar employs data from 64 countries. Medical resources are different within different areas resulting in biased reflection of pandemic severeness. In addition, three research focus on the first four months of COVID-19. Medical scarcity at the earlier stage may worsen pandemic as the medical resources per confirmed cases has significant negative effects on the coronavirus disease mortality rate [16]. This paper, on the other hand, uses data from a wider period. Hospitals would be more prepared to economically allocate medical resources as time goes by. Therefore, this paper employs daily confirmed cases for pandemic data.

Tourism, catering, and hospitality industries receive major strikes from contagious disease outbreaks. Kevin K and colleagues summarize Hong Kong hotel industry performances against SARS in 2003 and H1N1 swine flu in 2009. This report concludes that hotel, as a quarantine space and travel screening, significantly mitigates the impacts of epidemic. At the same time, it is reasonable to expect upgrading governmental requirements on hygiene surveillance improves hoteling condition [17]. And consequently, the systematic improvement could lead to better collaboration with the government which renders the hospitality industry a break under pandemic pressure. Olivier, D. records that over 3.6 million US$ loss in tourism stock market, 23% fall in Beijing hotel occupancy rate, and massive of restaurant vacancies in 2003 SARS. And after the pandemic, fast recovery follows [18].

However, the situation even worsened under COVID-19 due to a faster spread-out and over a longer time. Research reveals a significant adverse impact from COVID-19 on tourism and hospitality industry stock returns in the U.S. Moreover, both industries are elevated in the most severe outbreak period. In the following months, adverse effects of COVID-19 start to decrease due to the easing of lockdowns [19]. Dwiyanjana, S. and Meilani, I. suggest COVID-19 causes a significant stock price recreation in Indonesian hotel, tourism, restaurant, and sub-sector companies. compared to the time before COVID-19 [20]. This paper will explore the rate of return changes under COVID-19 pressure in mentioned industries in China where a stricter lockdown policy was announced.

To sum up, this paper builds on mentioned papers to explore return rate volatility and changes in Chinese tourism, catering, and hotel industry based on confirmed case data during COVID-19, aiming to demonstrate market changes over time and various pandemics severeness.

The following parts of this research are organized as below: Part 2 is research design which includes data source, data processing, stationary tests, and model specification; Part 3 is empirical results that include ARMA order-selection, VAR model results, and ARMA-GARCH model results; Part 4 is discussion which compares results from this research to former researchers', possible future research directions, insights to policymakers or investors and limitation reflections; last conclusion part summarizes prime results from this research.

2. Research Design

2.1 Data Source

Statistics of Chinses mainland's pandemic employed in this paper are derived from The National Health and Family Planning Commission of the People's Republic of China (NHFPC) websites while overseas cases are cited from World Health Organization (WHO) database. This paper cited both datasets from 23rd January 2020 when the pandemic first began. What is worth mentioning is that to eliminate impacts from the spring festival travel rush in China, both selected data sets end by 21st January 2021 instead of an entire year later. Two datasets summarize various relating aspects of pandemic stats including daily new cases, hospitalization, and death cases. This paper chooses daily new confirmed cases as the prime representation of the severeness of Covid-19.

For data from the selected stock market, figures are collected and summarized by Choice Finance website. Raw data about three industries namely, tourism, hotel, and catering, are all composed of stock prices. To be specific, the index for the travel industry takes 31 various stocks into account with weighted calculation. Chosen stocks are composed of one prime leading company of the industry which has a market value of over 100 billion Yuan (equally 14.8 billion USD.), several medium-sized market sharers within 10~70 billion Yuan range market values, and 25 less influential firms with the smaller scale of under 10 billion market values. Similarly, selected data for the hospitality industry and catering index conclude data of 7 and 13 companies, respectively. Reviewing all historical data from the three industries, this paper utilizes adjusted closing price as well as the rate of return. Adjusted closing price amends the stock's closing price and reflects its value after elucidating any corporate actions including dividends, stock splits, and rights offerings. The rate of return reveals net gain or loss in percentage of the investment's initial price. Both selected data assist this research to generate accurate forecasts on future market performance and fluctuation under Covid-19.

2.2 Data Processing

Stock indexes, as well as daily confirmed cases, are the main components of regression functions, however, further processing improves the dataset to better fit the regression model. To begin with, stocking statics are available only on trading days. Pandemic data within non-trading days are then omitted and rearranged by ascending date. Besides, logarithmic operations are introduced to reduce the heteroskedasticity of the chosen datasets. By doing so, all stats are also on a smaller scale and better suited for calculation. More importantly, for the rate of returns, this paper adds one to equations in advance to deal with relative stationary sequences that converge to zero.

Daily confirmed cases for domestic and global data, stock index, as well as stock returns for three industries, are taken as logarithmic terms defined as follows:

$$\ln Global\ Cases = \ln(1 + Global\ cases) \tag{1}$$

$$\ln Chinese\ Cases = \ln(1 + Chinese\ cases) \tag{2}$$

$$\ln Closing\ Price = \ln(1 + Closing\ Price) \tag{3}$$

$$\ln Return_t = \ln(1 + \frac{Closing\ Price_t - Closing\ Price_{t-1}}{Closing\ Price_{t-1}} \tag{4}$$

After proper calculation, generated stock series are plotted against time, displaying good

volatility. The first plot in Figure 1 as an example, shows ln (rate of return) for tourism stocks against time. Noticing the plots are on small scales with 0.05 as a unit on the y-axis, it is observed that variances are small, proving small volatility.

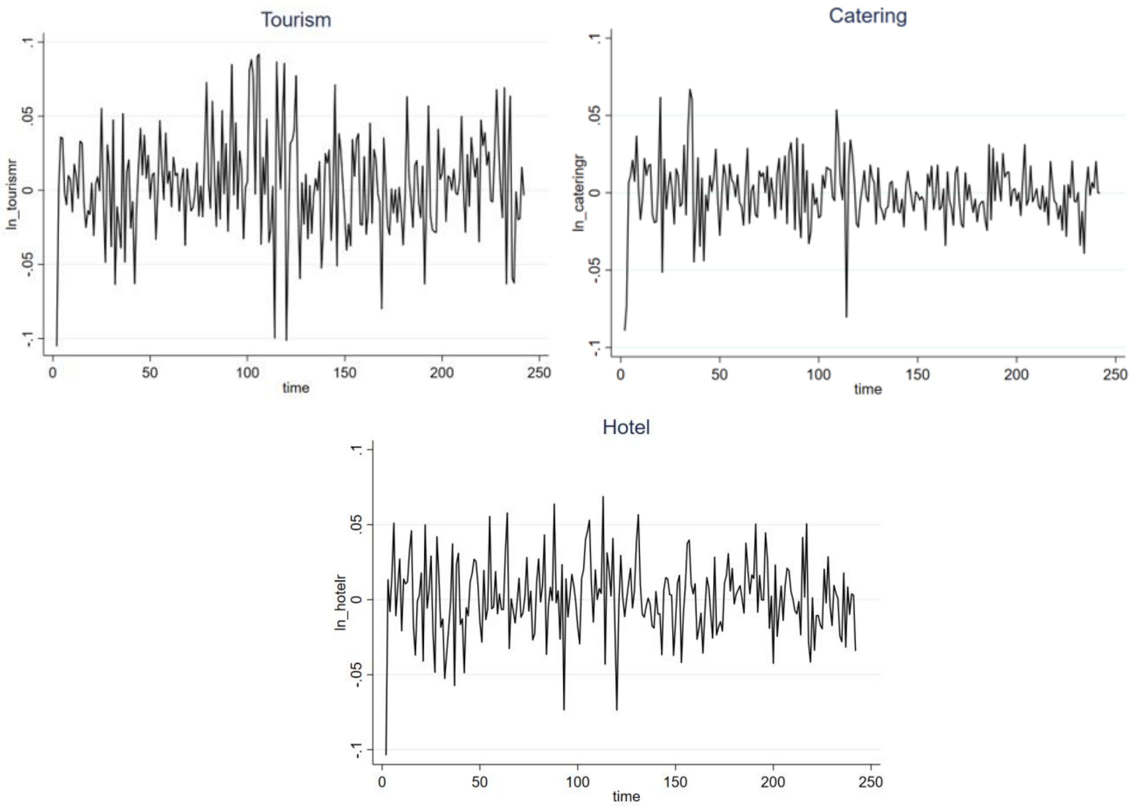

Figure 1 Data Visualization

2.3 Data Processing

Generating accurate results on stationary test is crucial before establishing a time series model. A Unit Root Test is then performed before starting the research to examine the stationarity of selected data series. Unit Root Process, a typical time series x_t is often be assumed as:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \Delta x_{t-i} + \varepsilon_t \tag{5}$$

ADF test are performed and summarized for all variables as shown in Table 1. The null hypothesis of the test is β=1, showing weak stationarity and the existence of a unit root.

Table 1 ADF test

Variables	t-statistic	p-value
Price(with ln)		
Tourism	-1.353	0.8742
Catering	-1.635	0.7783
Hotel	-2.104	0.5437
Newly confirmed cases		
China	-20.883^{***}	0.0000^{***}
Global	-3.841^{**}	0.0146^{**}
Yield		
Tourism	-11.792^{***}	0.0000^{***}
Catering	-12.675^{***}	0.0000^{***}
Hotel	-10.753^{***}	0.0000^{***}

Note: ***, ** and * indicate significant level of 1%, 5% and 10% accordingly.

It can be concluded from the table that poor stationarity showed in the ln (stock price) series, while yield stock stats in ln rate of returns are approved strong stationarity. Results for traveling catering and hotel stock index with logarithm are over 10% significant level. However, when considering the logarithmic processed rate of returns, improvements are obvious. P values of yield stock stats for three industries are all under 1% significant level, rejecting the null hypothesis.

For pandemic data, the logarithmic series for Chinese newly confirmed cases is even more stationary than that of global’ s stats. The stationary condition of the global confirmed cases series in logarithm term can be trusted under over 95% confidence intervals, while that of Chinese cases is within 99% confidence intervals. Therefore, this paper utilizes the prementioned stationary series of data, namely Chinese and global daily confirmed cases in logarithm, logarithmic rate of return of tourism, catering, and hospitality industries, to build the following models.

2.4 VAR Model Specification

Before building the ARMA model, Vector Autoregression (VAR) model is firstly built to assemble all three stocking variables and two pandemic data series into one single system. In this case with five variables, namely three stock rate returns, world, and Chinese new cases, VAR (p) model could be written as:

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{6}$$

Where y_t , $y_{t-1}, \dots, y_{t-p}$ include all five response variables in each time-series period. And $\Gamma_0, \Gamma_1, \dots, \Gamma_p$ are 5×5 coefficients matrixes. $\{\varepsilon_t\}$ is the vector white noise process.

Two major concerns arise when building a VAR model. How many endogenous variables (N) should be defined and what is the maximum lag order (p)? Akaike Information Criterion (AIC) and Schwarz Criterion (SC) are normally used to determine lagging order p:

$$AIC = \log\left[\frac{\sum_{t=1}^{T} e_t^2}{T}\right] \quad \text{for lag order } p \tag{7}$$

$$min\ \{AIC\} = \log\left[\frac{\sum_{t=1}^{T} e_{pt}^2}{\sum_{t=1}^{T} e_{(p+1)t}^2}\right] - \frac{2}{T} \quad \text{for lag order } p+1 \tag{8}$$

Equation (7) and (8) expresses two VAR model with lag order p and p+1. T is the total sample length. A reliably selected lag order p would be witnessed when a small difference between two calculated AIC is observed.

Likewise, for SC:

$$SC = \log\left[\frac{\sum_{t=1}^{T} e_t^2}{T}\right] + \frac{p\log \mathrm{T}}{T} \quad \text{for lag order } p \tag{9}$$

$$min\ \{SC\} = \log\left[\frac{\sum_{t=1}^{T} e_{pt}^2}{\sum_{t=1}^{T} e_{(k+1)t}^2}\right] - \frac{\log T}{T} \quad \text{for lag order } p+1 \tag{10}$$

A smaller difference between two calculated SC indicates a more accurate lag order p.

In addition, maximum lag order p could be determined by Likelihood Ratio (LR) expressed as:

$$LR = -2(LogL_p - LogL_{p+1}) \tag{11}$$

Where LR converges: $LR \sim X^2_{(N^2)}$, N is the number of endogenous variables in the model.

Lag order p would be considered small when LR surpasses the boundary value, indicating more lagging variables should be included as explanatory variables.

Arguably, VAR model is seldom considered theoretical based as no prior constraint to variables is required. Then to present estimation results of VAR, and more importantly, explore interaction within five variables, impulse response graphs are plotted. The impulse response function traces model dynamics paths of variables when exogenous impulses are introduced to the system, also known as Impulse Response Function, IRF.

$$\Psi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t'} \tag{12}$$

Equation (12) represents the impact on i^{th} variable, namely $y_{i,t+s}$, in period $(t+s)$ when the disturbance term ε_{jt} of j^{th} variable increases by 1 unit. Impulse graphs are plotted for three stocks against global and Chinese pandemic cases.

2.5 ARMA Model Specification

An ARMA model is a combination of autoregressive (AR) process and a moving average (MA) process. AR model forecasts based on past time-series data. The parameter p as the largest lag order of all lag terms in an AR(p) can be presented as follow:

$$y_t = \emptyset_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{13}$$

$\emptyset_0$ is a constant and ε_t is the error term in period t in time series y_t. MA model, also written as MA(q), predicts using current and past errors:

$$y_t = c_0 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{14}$$

c_0 is a constant and ε_t is the error term in period t in time series y_t. Noticeably, MA is always stationary as a linear combination of white noise series.

To fully consider how pandemic relates to stock market fluctuation in tourism, catering, and hotel industries, this paper builds an ARMA (p, q) model where p, q are integers ≥ 0. ARMA model combines both impacts from past socking values and past stochastic terms for forecasting.

$$y_t = \emptyset_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{15}$$

In equation (8), the dependent variable y_t is the logarithmic stock rate of return in period t. $\emptyset_0$ is a constant while $\{\varepsilon_t\}$ is a white noise series and ε_t is the error term. φ_i and θ_i are corresponding coefficients which can be defined in polynomials:

$$\Phi\,(L) = 1 - \varphi_1 L - \cdots - \omega_p L^P \tag{16}$$

$$\Theta(L) = 1 - \theta_1 L - \cdots - \theta_q L^q \tag{17}$$

2.6 GARCH Model Specification

Economists used to assume constant variance in time-series. However, intensive fluctuations within a certain period, which is also defined as volatility clustering, are more often witnessed in stocking markets. Engle introduced Autoregressive Conditional Heteroskedasticity (ARCH) model in 1982. Such process assumes the next period variance is high if the last period data has a high variance. Like AR, such an autoregressive logical process generates a more accurate variance forecast. Bollerslev improved the ARCH model by adding the GARCH term to the original model to form the Generalized ARCH (GARCH) model which is normally written as followed This process improves the accuracy of predicted conditional variance by reducing the number of coefficients used in the model. A GARCH (p, q) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \quad (18)$$

The constant term is α_0. σ_t is the forecast variance while ε_t is the actual variance in period t.

Considering risk as a vital part of stock markets and how they positively correlate to market returns, introducing ARMA-GARCH model better explains the volatility of the three chosen stock prices.

3. Empirical Results

3.1 ARMA Order-Selection

Establishing an ARMA model requires two order-selection steps for both AR and MA parts of the travel industry, hotel, and catering stocks. This paper first examines the Partial Autocorrelation Function (PACF) plot of the three data series and summarizes results generated from Stata. Then for MA part of the series, Autocorrelation Function (ACF) visualizes choices of the order of MA model. All results are concluded in Figure 3 as shown.

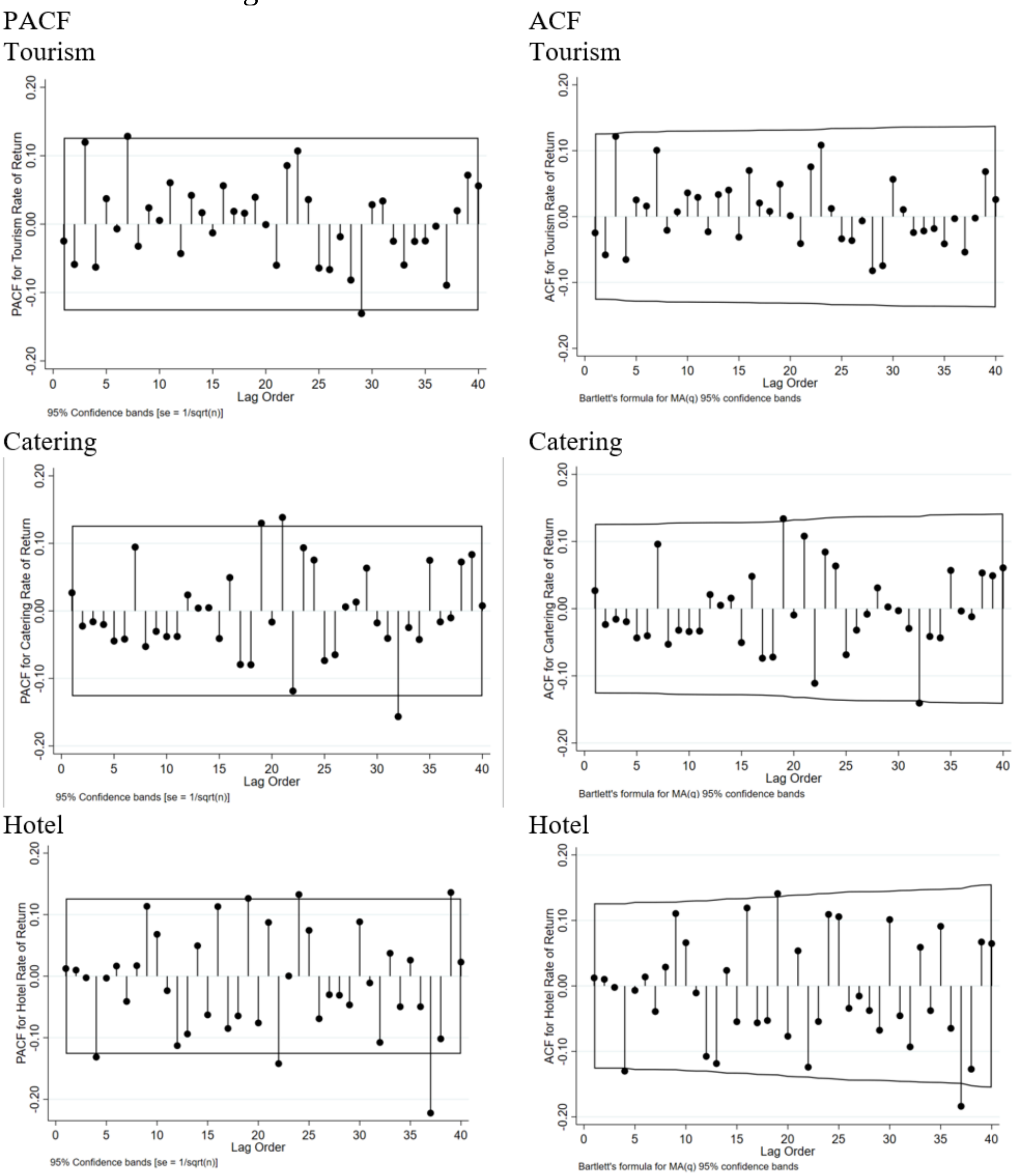

Figure 2 PACF and ACF

The rectangular space in both PACF and ACF plots benchmark suitable lag term numbers against 10% statistically significant level. Dots that outline the rectangle may have a significant impact on the chosen data series.

To summarize from the plots, for the tourism market, PACF result shows lag 7 and 28 terms of the original series may have a more significant impact on data while ACF gives no order. It can be seen from two plots in the second row that both PACF and ACF tests prove lag 19 and 33 terms are an ideal choice for ARMA process for catering stock indexes. In addition, lag order of 22 could also be considered significant in PACF test results. Then for the hotel industry, lag 4 and 37 terms are suitable for both AR and MA processes. Lag orders of 22, 24, and 39 also approved as significant for PACF while terming 18 for ACF.

This paper uses the smallest lag order possible to reduce complexity and uncertainty.

3.2 VAR Model Estimation Results

3.2.1 VAR order-selection

Five prementioned stationary series: pandemic data for both Chinese and global in logarithmic terms, logarithmic stock rate of returns for tourism, catering, and hotel industries. To generate order-selection results for a VAR (p) model, different VARSOC selection-order criteria are performed in Stata. Results are summarized in the table below:

Table 2 VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1881.01				5.3e-14	-16.3843	-16.3541	-16.3094
1	3108.83	2455.6	25	0.000	1.4e-18	-26.8893	-26.7079*	-26.4395*
2	3148.86	80.069	25	0.000	1.3e-18	-27.0206	-26.6879	-26.1959
3	3176.88	56.028	25	0.000	1.2e-18	-27.047	-26.563	-25.8474
4	3188.96	24.164	25	0.510	1.4e-18	-26.9341	-26.299	-25.0349
5	3219.69	61.452	25	0.000	1.3e-18	-26.9841	-26.1978	-24.8998
6	3272.14	104.9	25	0.000	1.0e-18	-27.2239	-26.2863	-24.4241
7	3285.6	26.922	25	0.360	1.2e-18	-27.1231	-26.0343	-24.6082
8	3374.6	178	25	0.000	6.7e-19	-27.6821	-26.442	-24.1783
9	3393.29	37.381	25	0.053	7.1e-19	-27.627	-26.2357	-24.1783
10	3402.48	18.392	25	0.825	8.2e-19	-27.4889	-25.9464	-23.6654
11	3469.18	133.4	25	0.000	5.8e-19	-27.8531	-26.1594	-23.6547
12	3501.49	64.604*	25	0.000	5.5e-19*	-27.9169*	-26.0719	-23.3436

It is observable from column ‘P’ in table that lag orders 1, 2, 3, 5, 6, 8, 11, and 12 are significant. Starting from lag order=12, this paper compares LR value and the threshold values at 5% significant level. The selected order is significant when rejecting the null hypothesis. Moreover, VAR stability is assessed by following the companion roots matrix. Repeating these steps, this paper utilizes VAR with 8 orders for following the modelling process.

3.2.2 Stability condition of VAR (8)

After estimating the parameters of VAR model, Stata was employed to evaluate the eigenvalue stability condition as shown in Figure 2.

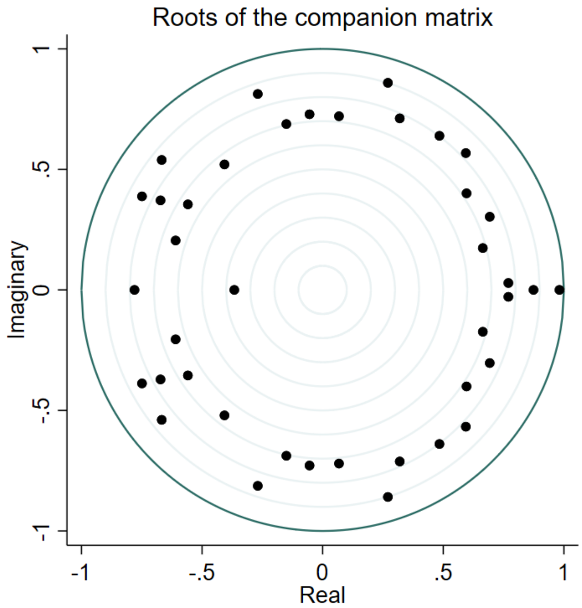

Figure 3 VAR StabilityA unite circle was drawn for results visualization. All dots indicate the eigenvalues locate within the circle, indicating estimation VAR (8) satisfies stability conditions.

3.2.3 Impulse response graph

Figure 3 summarizes all the impulse response results of variables, to be specific, tourism, catering, and hospitality stock returns in logarithm against domestic and global covid-19 newly confirmed cases in logarithm.

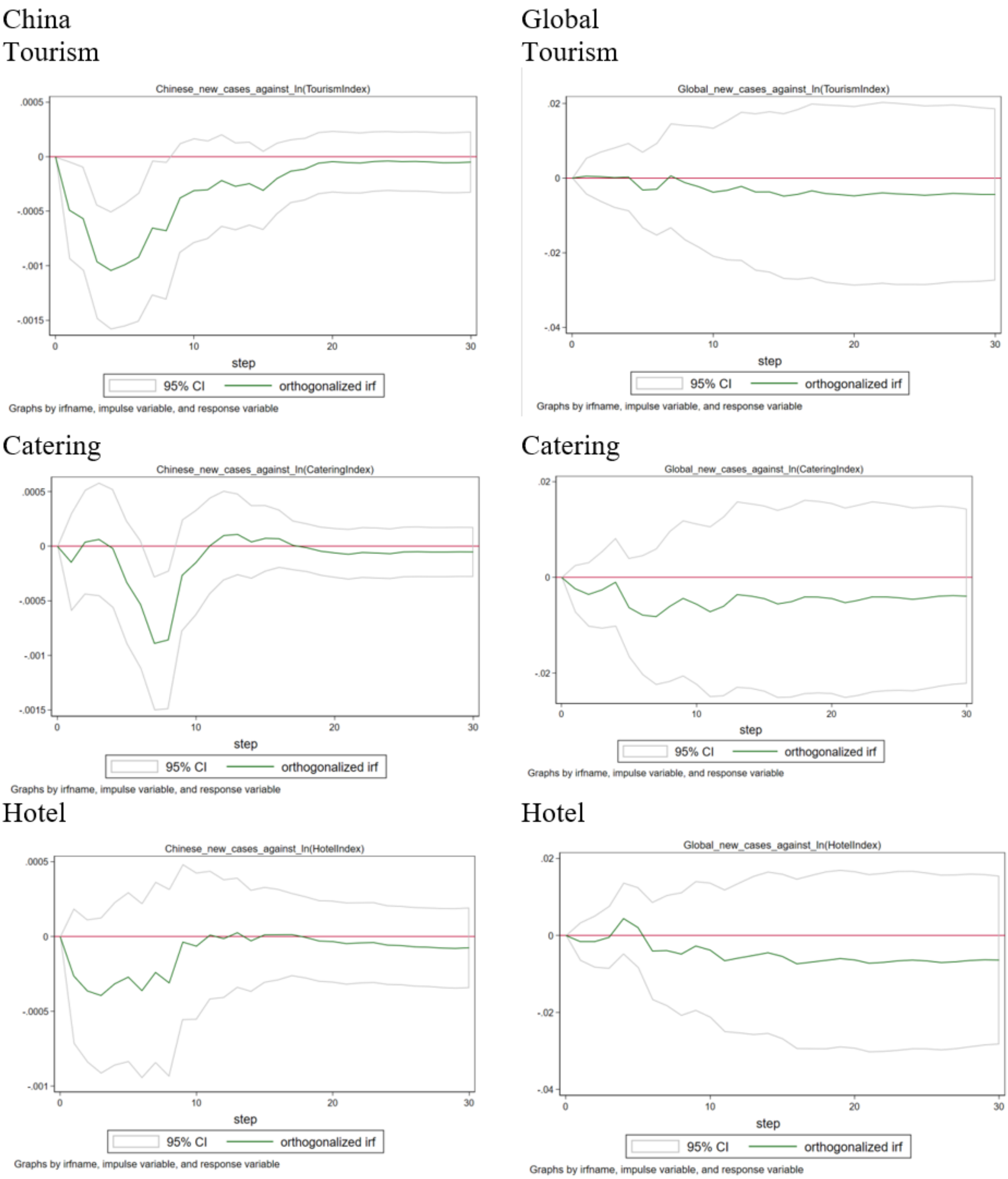

Figure 4 Impulse and response

Several observations could be drawn from the impulse response estimations (Please see Figure 4). To begin with where the pandemic's first outbreak and dynamic fluctuations in tourism, catering, and hotel stocking return rates that were witnessed by Chinses investors are more credibly to be an ephemeral impact. To be specific, in the first period where t=0, an additional percentage increase in Chinese daily cases will significantly lessen the rate of return in all three industries. Within the first 10 periods, a maximum of 1%, 1%, and 0.05% decreases are observed for the travel industry, catering, and hospitality industry respectively. Infectious disease has a severer influence on the tourism and catering industries. A mandatory quarantine policy might have presumably eased the pressure on hoteliers to some extent. Consequently, this resulted in more steady declines in the rate of return in hotel industry. After 10 periods, plotted lines all converge to zero as time goes by, meaning domestic daily new cases have lesser and lesser influences on the three industries. These patterns indicate once no massive outbreak of infection domestically tourism, catering, and hotel industries would only be minorly affected. Such results are good reveals of Chinese governing success in pandemic control and economic recovery.

In stark contrast, three stocks' rates of returns perform differently under pressures from global newly confirmed cases. On a humbler scale of 0.6%, global pandemic also negatively correlates with the observed stocks. However, impacts on all three markets were gradually expanded, followed by an even more gentle leveling off. Possibly, on average, a small percentage of overseas businesses result in less significant responses. In addition, the impact of overseas outbreaks on these three sectors is difficult to demonstrate in the short term. But an increase in the epidemic outside China will tangibly reduce the revenue from this part of the business eventually, regardless of the time lag.

3.3 ARMA-GARCH Estimation Results

Introducing a GARCH term when the existence of conditional heteroskedasticity is observed. Consequently, examining the variance condition of the stock rate of returns series is crucial when preparing to build an ARMA-GARCH model. See figure 1 for plots of used data series which reveal conditional heteroskedasticity.

Based on ARMA model results, this paper uses:

AR (7) - GARCH (1,1) model for the tourism market, with exogenous lag terms of Chinses or global confirmed cases.

AR (19) – GARCH (1,1) model for catering market, with exogenous lag terms of China's confirmed cases.

ARMA (19,19) - GARCH (1,1) model for catering market, with exogenous lag terms of global confirmed cases.

ARMA (4,4) - GARCH (1,1) model for hotel market, with exogenous lag terms of China's confirmed cases.

AR (4) - GARCH (1,1) model for hotel market, with exogenous lag terms of global confirmed cases.

This paper mainly focuses on the variance equation in the GARCH part to determine relations between Covid-19 and stock market volatility. Results generated from Stata are summarized below in Table 3.

Table 3 ARMA-GARCH estimation results, variance equation

	(1)	(2)	(3)	(4)	(5)	(6)
	Tourism		Catering		Hotel	
Newly confirmed cases						
China	3.3997		-1.8613		-1.1111	
	(4.8123)		(0.6787)		(0.7243)	
Global		0. 0475		-0.1946***		-0.0922
		（0.0764）		(0. 0387)		(0.0281)
GARCH (1, 1)						
ARCH (-1)	0.0935*	0.0963*	0.2201***	0.2040***	0.0343	0.0586**
	(0.0515)	(0.0534)	(0.0769)	(0.0741)	(0.0436)	(0.0258)
GARCH (-1)	0.7777***	0.7953***	0.3715	0.1257	-0.8073***	-0.9702***
	(0.1100)	(0.1164)	(0.2332)	(0.2202)	(0.1485)	(0.0401)
Constant	-47.4007	-9.796***	12.5136	-5.296***	5.6850	-5.3159
	(54.6526)	(1.4671)	(7.3599)	(0.5500)	(8.1402)	(0.4309)

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

Based on the table, at least one coefficient with under 1% significant level is observed in ARCH and GARCH rows. This proves that the volatility of the rate of returns has significant conditional heteroskedasticity, and consequently, approves ARCH or GARRCH modeling. To conclude from the other explanatory variables, modest increase in return rate volatility in the three sectors is witnessed under both domestic and global pandemic pressure.

4. Discussion

Results from this research advocate mainstream findings of how coronavirus adversely affected stock market fluctuation. In addition, this research finds that the Chinese tourism, catering, and hotel market experienced rapid and noticeable impacts from the domestic pandemic in the earlier phase, reinforcing most mentioned research. However, the effects of domestic new cases on the rate of returns gradually converge to zero. Such result disproves Alali's prediction of a long-lasting stock shock and expands Alfaro's discoveries of economic rebound once pandemic became less serious than anticipated in Chinese markets. GARCH model, similar approach approved by Nicholas' research, does not require to assume linearity, independence, and constant variance, which assists this paper to generate volatility results. Both Chinese and global pandemic stats make a small impact on return volatility in three industries. Also, investors could concern more about domestic stats as global pandemic data weakly affect the stock returns.

Apart from that, less considerable influence detected in hospitality approves expectation of hotel industry easing pandemic pressure. Relate more to policy making, results advocate empirics from H1N1 and SARS that improvements in hotel hygiene surveillance and collaboration could mitigate pandemic outbreaks.

Further research can be conducted by applying the same model to confirmed cases and deaths, respectively. By comparing results with former panel data results to find a more accurate regressor. This result also gives a brief reflection of how the lethality of contagious diseases varies with the outbreak stage. Moreover, since the influence of the pandemic decreases over time, adding another exogenous variable to search for a powerful indicator like the unemployment rate may complete the model.

5. Conclusion

This research employs an ARMA model to explore pandemic impacts on entertainment industry tock returns. A VAR system containing three collective stock returns and confirmed pandemic cases for China and overseas is utilized to deal with multivariable interactions. Then impulse response graphs are drawn for visualization and value demonstration. Finally, based on conditional heteroskedasticity in stock return series, this research builds an ARMA-GARCH to focus more on volatility which represents risks in stock industry. The research lays immense importance on impulse response graphs and GARCH part and draws following conclusions.

During COVID-19, Chinese tourism, catering, and hotel stock market returns are strongly adversely affected by domestic newly confirmed cases at the beginning of the pandemic, with hospitality being the least influenced. This impact decreases later in 2020 which may symbolize a governmental triumph against coronavirus. Global pandemic in comparison makes less impact due to limited overseas business. The research also proves zero correlation between pandemic and return rates' volatility. The results are appliable for investors and suggest great economic importance of manage COVID-19 outbreak for policymakers.

References

[1] Zhongming Z, Linong L, Xiaona Y, et al. COVID-19 impact on tourism could deal $4 trillion blow to global economy: UN report. 2021.

[2] Pendell D L, Cho C. Stock market reactions to contagious animal disease outbreaks: An event study in Korean foot-and-mouth disease outbreaks. Agribusiness, 2013, 29(4): 455-468.

[3] Chen C D, Chen C C, Tang W W, et al. The positive and negative impacts of the SARS outbreak: A case of the Taiwan industries. The Journal of Developing Areas, 2009: 281-293.

[4] Chen, M.H., Jang, S.S., Kim, W.G. (2007), The impact of the SARS outbreak on Taiwanese hotel stock performance: An event-study approach. International Journal of Hospitality and Management, 26(1), 200-212.

[5] Chen M H, Jang S C S, Kim W G. The impact of the SARS outbreak on Taiwanese hotel stock performance: an event-study approach. International Journal of Hospitality Management, 2007, 26(1): 200-212.

[6] Al-Awadhi A M, Alsaifi K, Al-Awadhi A, et al. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. Journal of behavioral and experimental finance, 2020, 27: 100326.

[7] Jianghuai Z F, Jin T. The Impact of the New Coronary Pneumonia Epidemic on the Consumer Economy and Countermeasures Analysis. J. Consumer Economics, 2020, 36(2): 3-9.

[8] Bash A. International evidence of COVID-19 and stock market returns: An event study analysis. International Journal of Economics and Financial Issues, 2020, 10(4): 34.

[9] Rehan M, Alvi J, Karaca S S. Short term stress of COVID-19 on world major stock indices. Asia-Pacific Financial Markets, 2022: 1-42.

[10] AlAli M S. The effect of who COVID-19 announcement on Asian Stock Markets returns: an event study analysis. Journal of Economics and Business, 2020, 3(3).

[11] Gil-Alana L A, Claudio-Quiroga G. The COVID-19 impact on the Asian stock markets. Asian Economics Letters, 2020, 1(2): 17656.

[12] Alfaro L, Chari A, Greenland A N, et al. Aggregate and firm-level stock returns during pandemics, in real time. National Bureau of Economic Research, 2020.

[13] Apergis N, Apergis E. The Role of Covid-19 for Chinese Pengembalian Sahams: Evidence from a GARCHX Model. Asia-Pacific Journal of Accounting and Economics, 2020.

[14] Ashraf B N. Stock markets' reaction to COVID-19: Cases or fatalities?. Research in International Business and Finance, 2020, 54: 101249.

[15] Aziz Jaafar N M, Noordin N. Panel regression method to analyse the stock market returns due to Covid-19. ESTEEM Academic Journal, 2021, 17: 166-181.

[16] Xie L, Yang H, Zheng X, et al. Medical resources and coronavirus disease (COVID-19) mortality rate: Evidence and implications from Hubei province in China. PLoS One, 2021, 16(1): e0244867

[17] Hung K K C, Mark C K M, Yeung M P S, et al. The role of the hotel industry in the response to emerging epidemics: a case study of SARS in 2003 and H1N1 swine flu in 2009 in Hong Kong. Globalization and health, 2018, 14(1): 1-7.

[18] Dombey O. The effects of SARS on the Chinese tourism industry. Journal of Vacation Marketing, 2004, 10(1): 4-10.

[19] Cepni O, Dogru T, Ozdemir O. The contagion effect of COVID-19-induced uncertainty on US tourism sector: Evidence from time-varying granger causality test. Tourism Economics, 2022: 13548166221077633.

[20] Nugroho D S, Pertiwi M I. Stock price reaction when covid-19 exist: moderating by firm's operating cash flow. Jurnal Ekonomi Malaysia, 2021, 55(1): 1-16.