A GARCH Framework Analysis of COVID-19 Impacts on SMEs Using Chinese GEM Index

Xuanyu Pan, Zeyu Guo, Zhenghan Nan, and Sangeet Srivastava

Abstract Stock market return analysis and forecasting are an important topic in econometric finance research. Since the traditional ARIMA models do not consider the variation of volatility, their prediction accuracy is not satisfactory to represent highly volatile periods of any stock market. The GARCH model family resolves the heteroskedasticity of a time series, and hence, it performs better in periods of high volatility. This paper explores the impact of the COVID-19 epidemic on Chinese small- and medium-sized enterprises (SMEs) using a GARCH model for Business as usual (BAU) simulation. We use the Chinese Growth Enterprise Market (GEM) stock index to represent the economic situation of SMEs during the COVID-19 period. Then, we extract, analyze, and predict changes in GEM stock volatility, explore the impact on and recovery status of SMEs, and predict their future trends. For BAU simulation, we first preprocess the GEM stock index between 2018 and 2020 and determine the order of autocorrelation and lags of the data to build the mean model. An ARCH effect test on the residual term of the mean equation was found to be significant and help to decide the order of the GARCH framework. Using the model, a BAU simulation was created and compared statistically with the actual GEM index during 2020. The comparison successfully demonstrated that the GEM index has increased volatility during the pandemic, which is in line with our prior hypothesis.

Keywords GARCH · BAU · COVID-19 · Chinese SMEs

1 Introduction

Beginning January 2020, the COVID-19 virus began spreading globally. According to Johns Hopkins University data [1], as of December 31, 2020, 1.8 million people have died worldwide from the COVID-19 virus. In China, the government decided to implement lockdown in cities to prevent the virus from spreading on a large-scale outside these cities. Starting February, schools were closed, factories were shut

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down, the whole society's production came to a standstill, and many companies were hit financially. COVID-19 occurred at a time when the Chinese economy was in a tightening phase of the business and financial cycle, which would have led to more severe economic losses [2]. China is a major manufacturing country, and factory shutdowns in China have simultaneously led to disruptions in the global supply chain, affecting everything from pharmaceuticals to apparel [3]. Studies show that every additional month of the epidemic costs 2.5% of global GDP [4]. The impacts were felt everywhere, though, measuring these impacts on stock indices is still a research question. Also, different industries were hit differently. To quantify these measures, simulation is the best tool. Theoretically, small- and medium-sized enterprises will be more negatively affected during an epidemic because they are smaller, have an unstable source of orders, and are more prone to capital chain breakdowns. When we reviewed the relevant research, we did not find any research on SMEs, and even if there were individual ones, they were not the quantitative analysis that we have expected [5, 6]. In that case, our research may fill this gap. We decided to study the impact of the pandemic COVID-19 on small- and medium-sized enterprises (SMEs) in China during the year 2020.

2 Data and Methods

We used the Growth Enterprises Market (GEM) Composite Index data procured from ex-ChiNext [7] to represent the economic situation of Chinese SMEs [8]. The GEM is designed by the Chinese government for entrepreneurial companies, SMEs, and companies in high-tech industries that are temporarily unable to be listed on the main board stock market, which includes 710 companies as of 2017 [7], so the GEM Composite Index is a fair indicator of the economic situation of Chinese SMEs. The China GEM Composite Index from June 21, 2018, to December 1, 2020, was extracted using the Tushare API of Tushare Big Data Community [9]. The period was chosen due to the limited availability of the dataset and also based on the assumption that this period is sufficient to represent the changes brought about by the COVID-19. Also, we split this dataset into two segments using threshold of January 1, 2020. We assume that before January 1, 2020, the stock index was unaffected by the outbreak of COVID-19, and after that date, it is affected by the outbreak. We further assume that from March 2020 through May 2020, return-to-work season does not eliminate the impact of the pandemic and that the impact persists until December 1, 2020. This study assumes that the change of volatility in China's GEM stock index is mainly affected by the pandemic and impacts due to the other factors which are negligible, and we investigated this by modeling the returns of the GEM index and its volatility under the assumption that the stock market is heteroskedastic.

In this paper, we model the GEM index using the GARCH model and its variants. The generalized autoregressive conditional heteroskedasticity (GARCH) model family evolved from Engle's ARCH model [10], proposed by Bollerslev [11], and

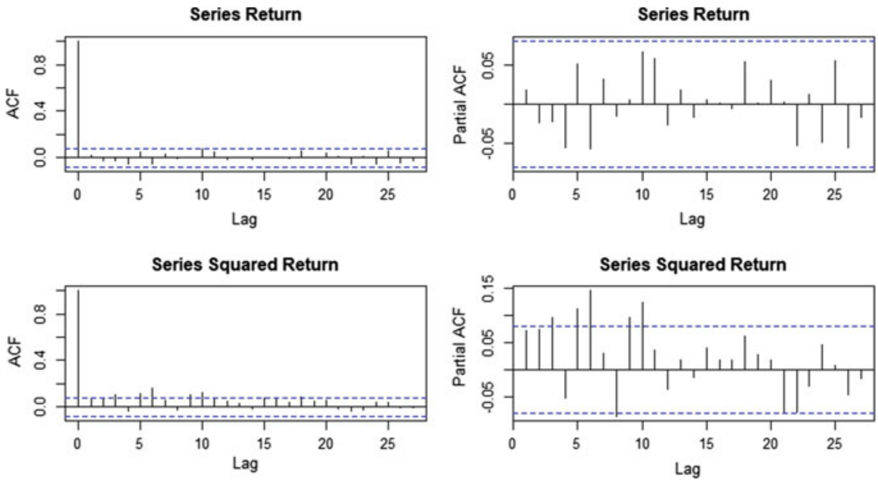

Fig. 1 ACF and PACF test

has been widely used in the financial analysis literature [12]. The model and its variants have also been used by many other studies [13–15], and they applied GARCH to detect changes in volatility due to epidemics with good performance. This paper followed these studies to apply this model to explore the impacts of COVID-19 on Chinese SMEs.

In this study, we used the classical GARCH model to represent volatility in stock indices. Before modeling the volatility, we simply used a stationary ARMA (1, 1) model to represent the mean, as ACF and PACF in Fig. 1 indicate that GEMCI has a weak autoregressive correlation. Equations. (1) and (2) represent the mean and variance equations used in the model.

$$\ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(1 + r_t), \quad r_t = \mu + \mathrm{AR} * r_{t-i} - \mathrm{MA} * a_{t-i} \tag{1}$$

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{2}$$

In this paper, we applied the GARCH model to two different periods, June 21, 2018, to January 1, 2019 (before the COVID-19 outbreak) to prepare the best model, and January 1, 2020, to December 1, 2020 (after the COVID-19 outbreak), to model the mean and variance of the two time periods. Then, we extended the model from the first period to the second period of January 1–December 1, 2020, as BAU simulation and compared it with the observed time series to derive the impact of the outbreak.

3 Results and Analysis

In the actual analysis stage, first, we need to fit the data using the GARCH model. We test the squared returns for the ARCH effect, and the results show that the Box–Ljung test score is 0.0003128 for an interval of 5 (Tables 1 and 2). This suggests that the returns are strongly autocorrelated and there is an ARCH effect, so the data are suitable for fitting with a GARCH model (Table 3). Next, we determined the model order to be (1, 1) using ACF and PACF tests. Then, we fit the GARCH (1, 1) model, and the results show that all parameters of the model are significant (Table 3) and the model to be well fitted (Table 4). We compared the AIC and BIC values at different orders by the information criterion and found that the GARCH performance did not improve significantly at different orders. We then performed an ARCH effect test on the residuals of the fitted model, and the results showed that the residuals no longer have an ARCH effect, suggesting to consider the residuals to be white noise.

Table 1 Box–Ljung test scores for ARCH effect of returns

	Returns	Squared returns
X-squared	4.3051	23.173
$d.f.$	5	5
p-value	0.5064	3.128×10^{-4}

Table 2 ARCH effect test for squared residuals

Box–Ljung test		
Data: squared residuals		
	Statistic	p-value
lag = 1	0.1314	0.71696
lag = 5	4.1452	0.23650
lag = 9	10.1207	0.04727

Table 3 GARCH model fitting result

GARCH model fit				
	Estimate	Std. error	t value	Pr(> |t|)
Mu	0.001204	0.000669	1.8002	0.071836
AR	−0.869344	0.113407	−7.6657	0.000000
MA	0.904952	0.097292	9.3014	0.000000
Omega	0.000013	0.000001	11.1058	0.000000
Alpha	0.078901	0.008938	8.8274	0.000000
Beta	0.879539	0.016457	53.445	0.000000

Table 4 GARCH model adjusted Pearson goodness-of-fit test

Adjusted Pearson goodness-of-fit test		
Data: GARCH model		
Group	Statistics	p-value ($g - 1$)
20	26.00	0.1302
30	28.85	0.4728
40	45.87	0.2087
50	48.69	0.4857

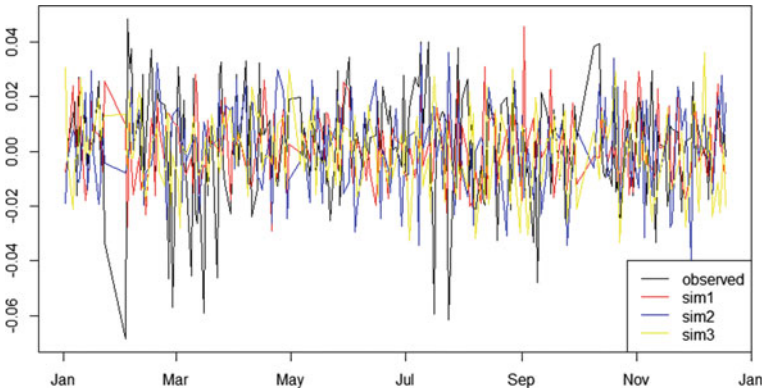

Fig. 2 2020 GEM simulated returns versus observed returns

Next, we used the fitted model to randomly simulate three different time series of the return of GEM index in 2020 and compared them with the actual GEM index in 2020, as shown in Fig. 2. We found that the observed time series (recorded data) has many downward spikes. The three simulations, on the other hand, are relatively stable and slightly above the black line. This suggests that in most cases, the observed returns are larger than the predicted returns, reflecting the increased volatility during the pandemic. However, this judgment is not straightforward, and we decided to quantify it. We calculated the mean of the three curves and obtained an averaged simulation to compare with the observed time series (Fig. 3). We calculated the mean and variance of the two time series and compared them. We can see in Table 5 the variance of the BAU is much smaller than the actual value, which proves that the pandemic did make the GEM index more volatile. And, the mean of BAU is larger than the actual value, which proves that the pandemic makes the return of the GEM index lower. We tested the significance of the differences between the means and variances of the two time series separately, and the results showed that the differences between their means and variances were significant.

In addition, several related studies have shown that pandemics lead to an increase in the RV and VIX indices, which implies an increase in market volatility and a rise

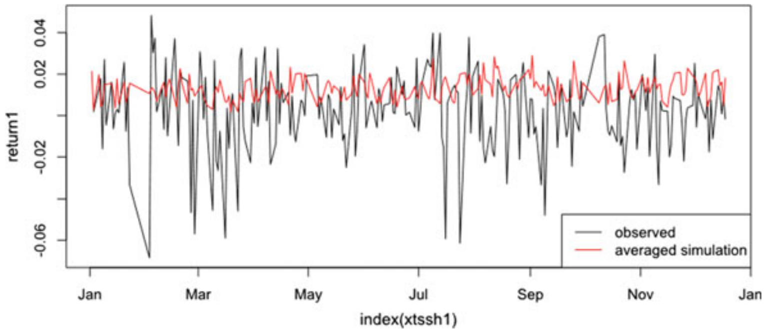

Fig. 3 2020 GEM mean simulated returns versus observed returns

Table 5 BAU versus actual returns

BAU versus actual returns		
Time series	Mean	Variance
BAU	0.0128065	$3.07 * 10^{-5}$
Actual return	0.001975034	$3.82 * 10^{-4}$
Significance of difference	t-score = 8.1555 p-value = $1.32 * 10^{-14}$	$F = 0.080285$ p-value < $2.2 * 10^{-16}$

in people's panic levels worldwide, which is consistent with our findings in China GEM [16–18]. Another paper also illustrates the trend of increasing risks in the world financial markets through volatility analysis [19].

4 Discussion and Future Work

The pandemic has impacted industries globally. As seen from the recorded data, it is found that the stock indices became more volatile during the year 2020. GARCH (1, 1) best-fit model successfully resolved the volatility that was extended further as simulated time series for the pandemic period. We compared the recorded data with that of simulated time series under business as usual volatility regime and found significant differences in the mean and variance of the two. Under the assumption of keeping other socioeconomic conditions constant for the year, the results showed that the volatility is higher for the recorded data for 2020 as compared to before the pandemic regime. Related studies show that the phenomenon of high volatility is usually associated with price level, the riskless rate of interest, the risk premium on equity, and the ratio of expected profits to expected revenues, and all four of these indicators are affected to some extent by the epidemic [20, 21]. This result could be further tested with more data for the other sectors as well as for different lockdown regimes during the pandemic event.

There are few limitations in the study. First, we can try some other variants of the GARCH model to represent the volatility of the financial market. In our study, we found that the two parameters of GARCH (1, 1) added up to close to 1. With other variants, we can increase the robustness given the condition alpha1 + beta1 = 1. We will also use other available data to confirm the robustness of our result. The data we used in this paper is Chinese GEMCI from June 21, 2018. We could try another time period, provided the data is available. Also, the China small- and medium-sized board index, and Shenzhen GEM 300 index, are good indicators for SME could be used to analyze the impacts.

Secondly, we assumed that January 1, 2020, is the start of the pandemic, and that the March 2020-May 2020 return-to-work season does not eliminate the impact of the epidemic and that the impact persists until December 1, 2020. This might not be accurate. To exclude possible error, we might choose more accurate boundaries and divide the period further, or take the consideration of the extent of COVID-19, such as numbers of cases and deaths.

Thirdly, the change in China's GEM stock index is mainly affected by the epidemic and other factors are negligible, may not be proper enough. To further confirm whether the large volatility changes we observe are linked to the novel coronavirus outbreak, we can segment to study the volatility at different periods after including significant socio-economic and political factors.

5 Conclusion

The findings suggest that GARCH (1, 1) has a better performance in portraying changes in SME volatility. This change may be associated with the outbreak of novel coronaviruses. Through segmenting the data and comparing the predicted GEM index values (BAU) in 2020 with its actual value, our model demonstrates that the COVID-19 does cause increased volatility in GEM.

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