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The Predictive Power of Implied Volatility and GARCH Forecasted Volatility During the COVID-19 Pandemic: Evidence from China's Stock Market

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Abstract: In this study, we explore how the performance of several popular historical and forward-looking forecasting measures for equity index volatility is affected by the COVID-19 related uncertainty. Our findings present convincing evidence for the advantages of implied volatility in predicting future volatility in the context of the COVID-19 pandemic. Our results also reveal that GARCH forecasted volatility contains unique information about market risk, but the information efficiency is sensitive to economic uncertainty. Therefore, the empirical evidence from China's stock market is supportive of a popular theoretical view that GARCH and implied volatility capture different aspects of market uncertainty and an appropriate combination of both measures may perform best in terms of information efficiency. This article contributes to the stream of post - COVID - 19 literature on its impact on financial markets and provides useful implications for financial practitioners.

Keywords: component; COVID - 19, Volatility Forecasting, GARCH, CSI 300, Implied Volatility, Encompassing Regression

1. Introduction

The COVID-19 outbreak is one of the most severe global sanitary crises in recent years. In the context of COVID-19, the financial markets recorded several shock waves and the impact of the pandemic may affect the financial market volatility even in the long run [1,2]. Accurate financial volatility prediction is an important financial task in many fields, such as portfolio rebalancing, analyses of return dynamics, derivatives pricing, and financial risk management. Thus, there are quickly growing studies on the impact of COVID-19 on financial market volatility (e.g., see [3-8]). Broadly speaking, two methods are widely adopted in literature to generate volatility forecasts [9]. The first approach is based on the historical market information about the variance of market returns, which is extracted by simple models. The second method is based on forward-looking expectations about future market volatility, which is extracted from observed option prices. For the historically-based dimension, since the pioneering studies by Engle [10] and Bollerslev [11], a large body of literature provides strong evidence that GARCH-type models are effective in predicting future volatility, as it captures various stylized facts of financial volatility and returns, such as leptokurtosis, long memory, leverage effects, and volatility clustering (e.g., see [12-14]).

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However, the GARCH model is based on historical information and is primarily a deterministic model. Thus, the information content of GARCH-type volatility is limited as it cannot capture the future perspectives of financial markets [15,16]. In contrast, as a forward-looking measure, an abundant literature has documented the implied volatility embedded in option prices contains more useful information about the forecasting of future volatility, as implied volatility reflects consensus expectations of professional investors for future market uncertainty and embeds views on nonlinear and asymmetric bets [17]. Therefore, since the seminal work by Black and Scholes [18], the implied volatility has been adopted and examined by vast empirical and methodological literature. For instance, Chiras and Manaster [19], and Day and Lewis [20] adopt the BS implied volatility as proxies for expected volatility and find evidence supporting the better forecasting ability compared with that of historical volatilities. Christensen and Prabhala [21], and Chiras and Manaster [19] find that implied volatility is better than historically-based models at forecasting future volatility and present if the options market is efficient, the implied volatility should subsume information contained in historical volatility. Using fuzzy approaches to option price modelling, the later studies show that the fuzzification of some key parameters in the Black-Scholes formula enables better forecasts for future volatility (e.g., see [22,23]).

However, several subsequent research contest this view, as the findings in these studies are subject to potential measurement errors due to maturity mismatch and overlapping samples problems [9], and favour that historical and forward-looking volatility capture different aspects of market risk. More recent studies support that the combination of the two types of measures has the best explanatory ability in predicting future market volatility [20,24], and owing to the dynamic nature of financial volatility, the predictive power of the GARCH and IV-based predictors should be examined under different market conditions [25-28].

To the best of our knowledge, there are only a handful of studies exploring how the COVID-19 pandemic affects the forecasting performance of both the historical and forward-looking dimensions in China's stock market. Therefore, our study is motivated by eliminating the research gap. Specifically, we try to answer the following question: (1) whether the GARCH forecasted volatility and implied volatility are informationally efficient for predicting future realized volatility, and (2) how the predictors perform differently in the different COVID-19 stages. To answer the research questions, we build upon previous studies and extend their analysis to investigate the impact of COVID-19 in several ways. First, we use the intraday realized volatility (**RV**) of the CSI 300 index as a proxy for the Chinese financial markets' volatility. The CSI 300 is designed to replicate the performance of the top 300 large-capitalization stocks in the Shenzhen and Shanghai stock markets [29]. Over the years, it has become the most widely used gauge of the Chinese stock market. Second, following Kelly et al [30], we use three forward-looking measures of the implied volatility, namely, ATM options (**IV**), the slope of implied volatility (**SLP**), the curvature of implied volatility smile (**CUR**), to capture the expected price risk, the asymmetric tail risk, and the downside tail risk respectively. We then adopt standard GARCH (1,1) volatility (**GAR**) as the historical measure. Finally, the information efficiency of both implied volatility and GARCH volatility are compared using univariate and encompassing regression analyses, which are commonly adopted in similar studies (see, e.g., [21,26,31,32]). Additionally, we are interested in the differences in their forecasting performances between the different COVID-19 stages.

This study focuses on the information efficiency and predicting performance of GARCH and implied volatility during the COVID-19 pandemic. Our findings present convincing evidence for the advantages of implied volatility in predicting future volatility in the context of the COVID-19 pandemic. Our results also reveal that GARCH volatility contains unique information about the market risk, but the information efficiency is sensitive to economic uncertainty. Therefore, the empirical evidence from China's stock market is supportive of a popular theoretical view that GARCH and implied volatility capture different aspects of market uncertainty and an appropriate

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combination of both measures may perform best in terms of information efficiency [20,24,26-28]. The main contribution of this study lies in examining the effect of COVID-19 on the information efficiency of both forward-looking and historically based measures under a unified framework and then contributing to the stream of post - COVID - 19 research on its impact on financial markets. The rest of the paper is organized as follows. Section 2 explains the sample period and specifies the variable construction. Section 3 presents the research methodology. In Section 4 we discuss the empirical results. Finally, Section 5 concludes this paper.

2. DATA AND SAMPLE

2.1. Key Dates and Periods

Our study period is from Jan 30, 2021, to Feb 23, 2022. By synthesizing existing studies [4,5,17,33-35], we split our sample into three periods. Each period is marked by a milestone that may bring structural a break to the financial market uncertainty.

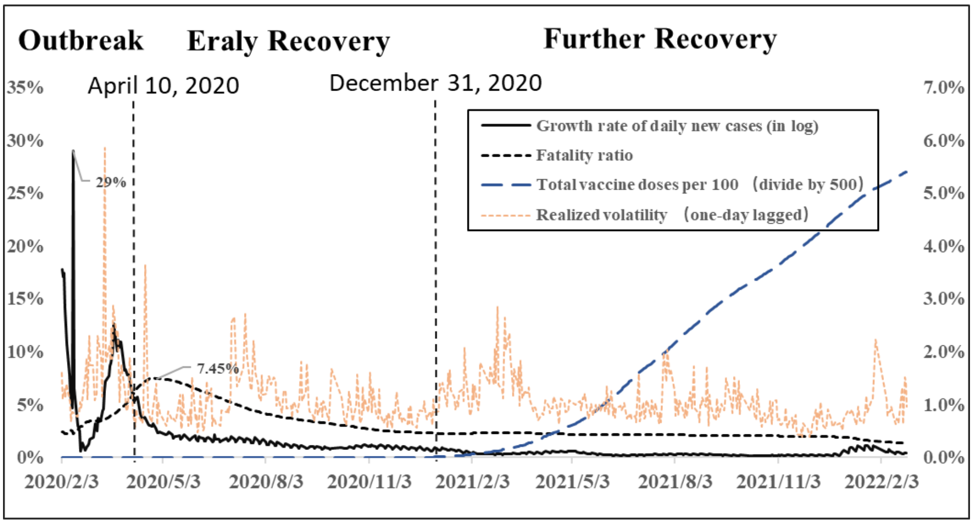

Figure 1: COVID-19 dynamics.

Figure 1 plots the evolution of the logarithmic growth rate of daily confirmed cases, the case fatality ratio, the total vaccine doses administered at the global level (per 100 population) and the intraday realize volatility of the CSI 300 index (one-day lagged). The vertical dash lines divide the sample period into the outbreak, the early recovery, and the further recovery period. The COVID-19 statistics are gathered from the WHO website.

The period between January 30, 2020, and April 9, 2020, is referred to as the outbreak period. The WHO declaration of the COVID-19 outbreak on January 30, 2020, signifies the beginning of this period. After that, the virus rapidly spreads and many Chinese local governments enforced complete lockdowns to control the outbreak. On March 11, the WHO declared the global pandemic. On 9 April, the Chinese government officially lifted all lockdowns and the infection rate and mortality rate of COVID-19 began to decline. During this initial crisis wave, the market volatility continued to increase and financial markets became more sensitive due to rising economic uncertainty [2,17].

The period from April 10, 2020, to December 30, 2020, is referred to as the early recovery period. This period begins with the Chinese official announcement of Phase 2 clinical trial of the COVID-19 vaccine and ends with the launch of a massive COVID-19 vaccination in China. The development of COVID-19 vaccines is considered to be the major approach to lower the risks of uncontrolled and unexpected growth of the pandemic. Existing studies suggest that any potential breakthrough during the development of the COVID-19 vaccination helps to stabilize the financial volatility (e.g., see [33,35]). Financial markets during this period are becoming more rational about the changes in the severity of the pandemic with still heightened volatility [34,36].

The period from December 31, 2020, to the end of the sample (23 February 2022), when China approved its first COVID-19 vaccine for general public use, is referred to as the further recovery period. Studies document that finical markets are sensitive to vaccine arrival rates. The massive COVID-19 vaccination assists in further stabilizing equity markets, and may bring the market volatility to pre-pandemic levels [33-35].

2.2. Volatility Measures and Forecasts

The dataset used in our study primarily consists of the SSE CSI 300 ETF options' daily closing data and high - frequency 5 - min closing data on the CSI 300 Index with the sample period running from February 3, 2020, to February 23, 2022, which are provided by the WIND terminal. **Figure.2** reports the time series of our market measures over the sample period.

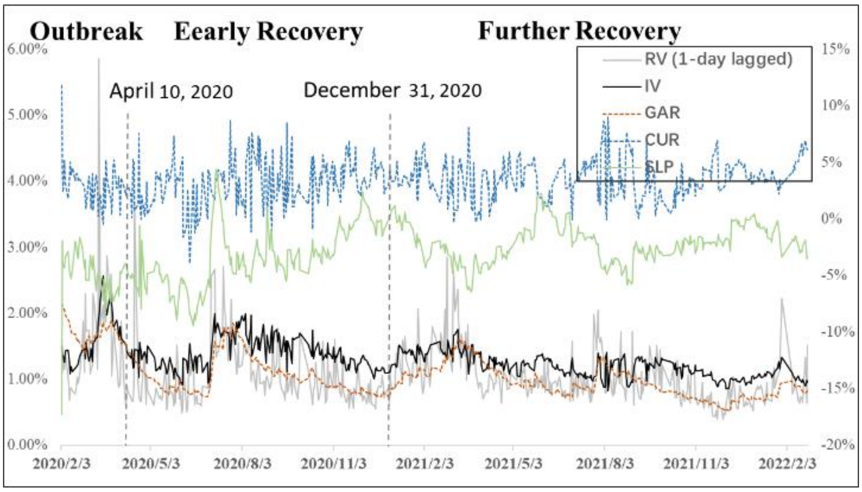

Figure 1: Time series of the market measures.

Following the common practice in the literature (e.g., [9,16,21]), we use one-day lagged realized volatility to quantify future volatility in the financial markets. This is given by the sum of the squared root of intraday returns sampled at equally spaced intervals, The intraday realized volatility (RV) is calculated as:

$$RV_t = \sqrt{\sum_{j=1}^{M} r_j^2} \tag{1}$$

Where M is equally spaced observation intervals (5 mins in this study), r_j is the log return of the observed period.

This study evaluates both historically-based and forward-looking volatility measures in terms of information efficiency. The historical volatility measure is constructed using the standard GARCH (1,1) model, which has been found to be the robust and appropriate specification in examining the information content of historical volatility (see, e.g., [15,32]).

The mean equation (2) for the GARCH model is specified as follows:

$$r_t = \mu + \varepsilon_{t,} \ \varepsilon_t \mid I_{t-1} \sim N(0, h_t) \tag{2}$$

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where h_t represents the conditional variance of the return series r_t, and $N(\cdot,\cdot)$ is a normal distribution. Under GARCH (1,1) model, the conditional variance of the return at period t+1 is predicted by the equation (3):

$$h_{t+1} = a_0 + \beta_1 h_t + \beta_2 \varepsilon_t^2 \quad (3)$$

where $\alpha_0>0$, $\beta_1>0$, and $\beta_2>0$. We use daily log index returns over the last 250 trading days to estimate the parameters in our GARCH (1,1) model and we forecast one day ahead. The forecasted volatilities (GAR) are given by the squared root of the forecasted conditional variances.

We then adopt three option-based variables widely used in the literature as the forward-looking variables (e.g., see [17,29,30]). These variables, the at-the-money implied volatility (IV), the IV slope (SLP) and the curvature of IV smile (CUR), capture the price risk, the asymmetric tail risk, and the downside tail risk respectively. The variables are extracted from the next calendar month's SSE CSI 300 ETF option contracts and measured using the option's Black–Scholes IV.

The first variable, the implied volatility of ATM options (IV), is computed as *the mean IV of the at-the-money options* (the moneyness of option contracts K/S_0 =1), which represents the uncertainty of price changes. The second variable, the curvature of the implied volatility smile (CUR), is calculated as $0.5 * (IV\ 10\%_{OTM\ PUT} + IV10\%_{OTM\ CALL}) - IV_{ATM}$ *(i.e., IV)*, which represents the differences between the cost of upside and downside tail risk. The 10% OTM denotes the moneyness of option contracts K/S_0 = 0.9 or 1.1. The third variable, the IV slope (SLP), is computed as $IV\ 10\%_{OTM\ PUT} - IV_{ATM}$, which represents the cost of protection against downside tail risk.

3. METHODOLOGY

Our first research question is related to the information content of the market measures. We employ univariate and encompassing regressions to examine their predicting performance as in the index studies by Jiang and Tian [31], Ederington and Guan [26], Christensen and Prabhala [21], and Canina and Figlewski [37].

The information content of each volatility predictor is assessed using the following univariate regression:

$$RV_t = \alpha + \beta x_{t-1} + \varepsilon \quad (4)$$

where x denotes the explanatory variables, the GARCH volatility (GAR), the implied volatility (IV), the curvature of IV smile (CUR) and the IV slope (SLP). Equation (4) allows us to examine two hypotheses. The first hypothesis is that the variable has explanatory power in predicting future realized volatility. If the first hypothesis is true, we would expect the β-estimates are significantly greater than zero, and the higher adjusted-R^2 from regression indicates the variable has more explanatory power. Using Wald statistics we can check the second hypothesis, that is, the variable is an unbiased estimator of future realized volatility. If the second hypothesis is correct, we would expect the $\alpha = 0$ and $\beta = 1$.

We then run the following "encompassing" multiple regression to analyze the predicting performances of the combination of the variables and the relative importance of the variables. The most general encompassing regression specification is:

$$RV_t = \alpha + \beta_1 x_{1.t-1} + \beta_2 x_{2.t-1} + \cdots \beta_i x_{i.t-1} + \varepsilon \quad (5)$$

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Where $x_1...x_i$ is our market measures. Similar to the univariate regression, Equation (5) allows us to examine the explanatory power of the combination of the independent variables. The relative importance of the variables can be assessed by the β-estimates, $\beta_i = 0$ suggests that the variable i does not contain useful information distinct from the other variables in predictive future realized volatility and therefore is redundant. Furthermore, if the joint null hypothesis 'H0: $\beta_i = 1$, and other β-estimates = 0' cannot be rejected by the F-test, we then conclude that the variable x_i subsumes all information contained in the other variables. Finally, by comparing the differences in prediction abilities in each COVID-19 period, we answer our second research question, that is, how the predictors perform differently in the different COVID-19 stages.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 1 reports the summary statistics for the market measures in the three sample periods. Two main observations can be made from the statistics. First, the mean GARCH and implied volatility forecasts are statistically larger than the mean future realized volatility, which indicates that the GARCH and implied volatility tend to be upward-biased. Interestingly, our empirical results suggest the IV is an unbiased estimator for the future realized volatility in the outbreak period when forecasting one day ahead. We conjecture that, as COVID-19 has started to grow rapidly, the economic uncertainty which has been contained in the option prices has dominated the market volatility and enhanced the unbiasedness of implied volatility.

Table 1: SUMMARY STATISTICS.

Period		**Outbreak**	**Early Recovery**	**Further Recovery**
Observations		48	177	276
RV	mean	1.49%	1.03%	1.01%
	std	0.85%	0.45%	0.38%
IV	mean	1.65%	1.37%	1.15%
	std	0.45%	0.28%	0.17%
SLP	mean	4.70%	3.24%	2.14%
	std	1.58%	2.76%	1.65%
CUR	mean	2.86%	3.19%	3.58%
	std	1.42%	2.19%	1.72%
GAR	mean	1.95%	1.23%	1.18%
	std	0.34%	0.36%	0.23%

* RV is one-day lagged

Second, the mean values of RV, IV and SLP exabit a downward trend, while CUR shows an upward trend as the pandemic subsidies, which suggests that the structural changes may exist in the market risks and in the investors' expectations about the future price uncertainties. This finding is supportive of the efficient market view that a market responded to the unfolding of information about the pandemic in a calibrated manner [17].

Table 2 presents the correlations between the realized volatility and the market measures. As we can see, the IV and RV maintained high correlations over all the sample periods. All the correlation coefficients of option-based measures are more pronounced during the COVID-19 outbreak. But the SLP and CRV are noticeably less correlated with realized volatility (30.0%, -26.1%). The relatively low correlations between option-based predictors indicate that they measure different aspects of market uncertainty. We then expect that the CUR and SLP provide complementary information about

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future volatility. The GARCH volatility has the smallest correlation coefficient (7.1%) in the outbreak period, while it exhibits a significant positive association with RV after that, and shows the largest correlation (66.0%) in the further recovery period, which implies that the information efficiencies of GARCH volatility may be significantly different between the COVID-19 outbreak period and the following periods.

Table 1: CORRELATIONS

Outbreak	**RV**	**IV**	**SLP**	**CUR**	**GAR**
IV	48.6%		67.6%	-43.5%	26.7%
SLP	30.0%	67.6%		-10.3%	17.7%
CUR	-26.1%	-43.5%	-10.3%		2.9%
GAR	7.1%	26.7%	17.7%	2.9%	
Early Recovery	**RV**	**IV**	**SLP**	**CUR**	**GAR**
IV	52.3%		-17.8%	-28.3%	60.1%
SLP	-11.2%	-17.8%		-19.6%	-33.4%
CUR	-2.1%	-28.3%	-19.6%		5.1%
GAR	50.4%	60.1%	-33.4%	5.1%	
Further Recovery	**RV**	**IV**	**SLP**	**CUR**	**GAR**
IV	60.0%		17.0%	-50.2%	76.6%
SLP	23.6%	17.0%		6.2%	36.1%
CUR	-12.1%	-50.2%	6.2%		-8.5%
GAR	66.0%	76.6%	36.1%	-8.5%	

* RV is one-day lagged

5. Regression Results

The univariate and encompassing regression results are shown in **Table 3**. For each regression, we report the coefficients, the model adjusted-R^2 and the significances. The p-values for the joint hypothesis test of 'H0: α= 0 and β = 1, or H0: β_i = 1 and other β-estimates = 0' will be reported in the analysis (not included in Table 3).

Panel A of Table 3 provides the results for the outbreak period. As can be seen, all coefficients for forward-looking measures are statistically significant, while the coefficient for the historical measure is statistically insignificant in this period. The univariate regression (1) shows that the coefficient for implied volatility is significant at 1% level and, as established previously, the F-test cannot reject the unbiasedness hypothesis of 'H0: α= 0 and β = 1' (p-value 0.344), which denote IV is an unbiased estimator for future realized volatility. The coefficients for the other option-based measures (SLP for downside tail risk and CUR for asymmetric tail risk) are statistically significant in the univariate regressions (2) and (3) but have significantly lower goodness of fit than that of implied volatility. As noted in Section 4.1 above, the correlation coefficient between GAR and RV in the breakout is only 7.1%, thus it is not surprising that the GARCH volatility loses its significance. To test the relative importance of the variables, we examine the results for the encompassing regressions (5) to (8). It is clear that the partial effect of adding other explanatory variables on implied volatility is negative, and the joint hypothesis 'H0: β_{IV} = 1 and other β-estimates = 0', is not rejected by the F-tests for (5), (6), (8) (p-values 0.507, 0.657, 0.785 respectively). These results together suggest that the information of other predictors is already contained in the implied volatility. To conclude, our results support that implied volatility extracted from option prices has the superior predictive ability for future realized volatility during the COVID-19 outbreak, while historically-

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based volatility tends to be inefficient under the same stressful situation. The results are generally in line with the findings of Li et al. [38], Vera-Valdes [39], Davidovic [40], and Iyer and Simkinsb [34].

The regression results for the early recovery period are presented in **Panel B of Table 3**. As is evident from regression (1), the implied volatility retains its significance but is biased, as the joint hypothesis of 'H0: $\alpha = 0$ and $\beta = 1$' is rejected for 0.00%.

Table 2: THE UNIVARIATE AND ENCOMPASSING REGRESSION RESULTS

Panel A. Outbreak		**Intercept**	**IV**	**SLP**	**CUR**	**GAR**	**ADJ.R^2**
Reg.1	IV	-0.0001	0.9132***				0.219***
Reg.2	SLP	0.0073*		0.1621**			0.070**
Reg.3	CUR	0.0194***			-0.1573*		0.048*
Reg.4	GAR	0.0115				0.1754	-0.017
Reg.5	IV+GAR	0.0024	0.9448***			-0.1560	0.206***
Reg.6	IV+SLP+CUR	0.0017	09104**	-0.0176	-0.0326		0.188***
Reg.7	SLP+CUR+GAR	0.0107		0.1463*	-0.1410	0.0736	0.086*
Reg.8	IV+SLP+CUR+GAR	0.0036	0.9532**	-0.0199	-0.0260	-0.1397	0.172**
Panel B. Early Recovery		**Intercept**	**IV**	**SLP**	**CUR**	**GAR**	**ADJ.R^2**
Reg.1	IV	-0.0011	0.8317***				0.269***
Reg.2	SLP	0.0109***		-0.0182			0.007
Reg.3	CUR	0.0104***			-0.0043		-0.005
Reg.4	GAR	0.0025**				0.6309***	0.249***
Reg.5	IV+GAR	-0.0018	0.5482***			0.3716***	0.322***
Reg.6	IV+SLP+CUR	-0.0031	0.9004***	0.0027	0.0292**		0.279***
Reg.7	SLP+CUR+GAR	0.0021		0.0091	-0.0075	0.6567***	0.246***
Reg.8	IV+SLP+CUR+GAR	-0.0035*	0.6119***	0.0115	0.0178	0.3655***	0.319***
Panel C. Further Recovery		**Intercept**	**IV**	**SLP**	**CUR**	**GAR**	**ADJ.R^2**
Reg.1	IV	-0.0049***	1.3082***				0.360***
Reg.2	SLP	0.0089***		0.0541***			0.052***
Reg.3	CUR	0.0110***			-0.0267**		0.011**
Reg.4	GAR	-0.0028***				1.0871***	0.434***
Reg.5	IV+GAR	-0.0051***	0.4989***			0.7981***	0.453***
Reg.6	IV+SLP+CUR	-0.0095***	1.5123***	0.0239**	0.0491***		0.408***
Reg.7	SLP+CUR+GAR	-0.0021**		0.0009	-0.0145	1.0757***	0.434***
Reg.8	IV+SLP+CUR+GAR	-0.0065***	0.6722***	0.0063	0.0151	0.6909***	0.452***

*, **, *** denote significant at 10%, 5%, 1% respectively. The P-values for the joint hypothesis test of 'H0: $\alpha = 0$ and $\beta = 1$, or H0: $\beta i = 1$ and other β-estimates = 0' will be reported in the analysis (not included in Table 3).

The other option-based measures, SLP and CUR lose their significance during this period. Notably, the adjusted-R^2 of regression (4) using GARCH volatility as the explanatory variable is 24.9% and significant at 1% level, which indicates that the GARCH volatility regained its predictive power and contains substantial information about future realized volatility. To get together, the findings provide evidence that the market volatility is no longer dominated by the investors' fear of crash risk related to the COVID-19 severity which is contained in the option prices, and the historical volatility became informative in explaining future volatility. This finding could also be backed up by the results of the encompassing regressions (5) to (8) in Panel B. As can be seen from the encompassing regression (5), the outperformance of implied volatility combined with historical volatility in predicting future volatility suggests that GARCH volatility contains incremental information beyond the forward-looking variables. The negative incremental adjusted-R^2 resulting from adding the CUR and SLP variables to the regression (5) indicates that the information of CUR and SLP were subsumed by implied volatility and GARCH volatility.

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The results for the further recovery period are presented in **Panel C**. The adjust-R^2 of univariate regressions (1) and (4) suggest that the predictive power of both GAR and IV remains higher in the further recovery period than in the previous periods. It is worth noting that the significantly higher adjust-R^2 (0.434) of univariate regression (4) suggests the GARCH volatility based on historical daily stock returns is more informative than the forward-looking measures extracted from option prices in forecasting future volatility. The outperformance of GARCH volatility over implied volatility can also be evident from the negative or small incremental adjusted-R^2 resulting from including option-based measures to GARCH volatility. However, the F-test of univariate regressions (4) rejects the unbiasedness hypothesis at significance of 1%. The encompassing regressions (6) to (8) show that the CUR and SLP are subsumed in GARCH rather than IV, which may imply the tail risk has been contained in the current volatility level as the COVID-19 related uncertainty decreases. And similar to the previous period, the regression (5) using the combination of IV and GARCH gives the best predicting performance, and the significant β coefficients for both GARCH and implied volatility suggest that the two variables contain different information.

To summarize, we draw the following conclusions: (a) as indicated by our regression results, ATM implied volatility contains the most useful information in predicting future volatility under the economic uncertainty related to the COVID-19 outbreak, while historical volatility is less efficient under the same stressful situations; (b) GARCH volatility contains unique information beyond those forward-looking measures but is sensitive to the market condition as GARCH volatility loses its predictive ability during the COVID-19 outbreak, whereas, exhibits the best predicting ability during the further recovery period; (c) not as we expected, the other option-based measures (CUR for tail risk and SLP for asymmetric risk) provide little incremental information in predicting future realized volatility during our sample periods.

6. CONCLUSIONS

In this study, we explore how the performance of several popular historical and forward-looking forecasting measures for equity index volatility is affected by the COVID-19 related uncertainty. Our test results present convincing evidence for the advantages of implied volatility in predicting future volatility in the context of the COVID-19 pandemic. Our results also reveal that GARCH forecasted volatility contains unique information about the market risk, but the information efficiency is sensitive to economic uncertainty. Therefore, the empirical evidence from China's stock market is supportive of a popular theoretical view that GARCH and implied volatility capture different aspects of market uncertainty and an appropriate combination of both measures may perform best in terms of information efficiency. This article contributes to the stream of post - COVID - 19 literature on its impact on financial markets and provides useful implications for financial practitioners. Further research is needed to examine the dynamic relationship between COVID-19 and the prediction ability of the market measures and to explore factors influencing their information efficiency.

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