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Research Article

Geopolitical Risk and Stock Market Volatility in Emerging Economies: Evidence from GARCH-MIDAS Model

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Previous studies have found that geopolitical risk (GPR) caused by geopolitical events such as terrorist attacks can affect the movements of asset prices. However, the studies on whether and how these influences can explain and predict the volatility of stock returns in emerging markets are scant and emerging. By using the data from China's CSI 300 index, we provide some evidence on whether and how the GPR factors can explain and forecast the volatility of stock returns in emerging economies. We employed the GARCH-MIDAS model and the model confidence set (MCS) to investigate the mechanism of GPR's impact on the China stock market, and we considered the GPR index, geopolitical action index, geopolitical threat index, and different country-specific GPR indices. The empirical results suggest that except for a few emerging economies such as Mexico, Argentina, Russia, India, South Africa, Thailand, Israel, and Ukraine, the global and most of the regional GPR have a significant impact on China's stock market. This paper provides some evidence for the different effects of GPR from different countries on China's stock market volatility. As for predictive potential, GPR_{Act} (geopolitical action index) has the best predictive power among all six types of GPR indices. Considering that GPR is usually unanticipated, these findings shed light on the role of the GPR factors in explaining and forecasting the volatility of China's market returns.

1. Introduction

As a global phenomenon, geopolitical risk (GPR) has long been considered as a major factor that influences the business cycle and financial markets. With the rapid development of information technology, the stock transaction has become easier and stock prices have become more sensitive to the revelation of GPR shocks. The GPR can affect the stock market in many ways. First, as uncertainty, the increased GPR will delay the decision-making process of the market participants. Second, the increased GPR can also push up the firms' costs by negatively affecting both demand and supply channels. Third, the increased GPR will also increase the risk of investment in the financial market. Geopolitics [1] justifies the importance of GPR on financial markets by emphasizing its economic and political role among countries. After that, several researchers attempted to verify this by checking the general impact of terrorism, wars, and military assaults on different macroeconomic variables [2, 3]. Until this day, when market participants are to make investment decisions, they always regard GPR as one of the most important determinants [4]. The global investors' survey (2018) by PwC reported that GPR is one of the key determinants when market participants making their investment decisions. Given that the current global GPR has become higher than ever before, governments, investors, and scholars pay more and more attention to the consequences caused by GPR [5]. Some studies have investigated the relationship between the stock market and GPR in developed economies such as European countries and the

USA [6, 7]. Although the developed economies have their dominance in global financial markets, the role emerging economies played in global economic development is increasingly important. The emerging economies faced global as well as regional GPR shocks, which could cause a series of consequences for business cycles and financial markets. Therefore, an increasing number of studies focus on emerging economies such as the BRICS [8–10] and others [11–13] considered 22 emerging markets that are Brazil, Chile, Colombia, Mexico, Peru, Czech Republic, Egypt, Greece, Hungary, Poland, Russia, South Africa, Turkey, China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan, and Thailand. Bouras et al. [14] considered 18 emerging markets that are Turkey, Mexico, Korea, Russia, India, Brazil, China, Indonesia, Saudi Arabia, South Africa, Argentina, Colombia, Venezuela, Thailand, Ukraine, Israel, Malaysia, and the Philippines), and these studies show the predictive potential of GPR for the stock index in emerging markets and argue that GPR has a more profound influence on the volatility of the stocks rather than returns.

As the world's largest emerging economy, China has grown rapidly in terms of trade and investment. Moreover, after the recent global COVID-19 outbreak, China is the only major economy with positive economic growth. More and more companies in China are going public to raise capital, and it is being anticipated that China will surpass the USA in the equity market [9, 10]. Chinese stock markets are closely related to the emerging Asian stock markets since it is the major trading partner of emerging Asia. Financial volatility is always an important feature in financial assets, and stock volatility plays an important role in portfolio management, asset valuation, hedging strategies, and risk management [15]. Therefore, looking at the volatility of China's stock market is quite imperative. The explaining and forecasting ability of regional and global GPR is particularly important for China because the financial system of emerging markets is usually subject to their exposure to GPR [4, 8].

Against this backdrop, previous literature has built up a preliminary foundation for GPR's predictive potential for the stock market. The theoretical framework can be traced back to the works of Sharpe [16], Eugene and French [17], and Frey and Kucher [18], which argue that historical events are reflected in asset prices. Following this framework, studies turned their interest into the influences of traditional macroeconomic variables, such as real GDP growth rate, industrial production growth rate, and unemployment rate, and macroeconomic uncertainty variables, such as economic policy uncertainty, GPR, and infectious disease pandemic on stock returns (see [11, 12, 19], among others) and volatility of stock returns (see [20–24], among others).

Since China put forward the "Going Global Strategy" for enterprises in 2002, China's overseas investment has grown rapidly. On the basis of the "One Belt, One Road" (OBOR) initiative in 2013 and the deepening of supply-side reform in 2015, China has become the economy with the fastest overseas investment. In 2016, China's outward foreign direct investment (OFDI) had exceeded foreign direct investment (FDI) for the first time and officially became the economy with net outward FDI. Although the growth rate of China's OFDI has slowed down in recent years, China has also begun to advocate the "Inner Circle" plan and focus on domestic investment; the current size of China's OFDI is still very large. According to the report on the development of China's outward investment and cooperation released by the Ministry of Commerce of China in 2020, China's OFDI ranked the top three in the world for eight consecutive years from 2012 to 2019, during which time, the global average proportion of China's OFDI reached nearly 10%. Therefore, under the current size of China's OFDI, geopolitical risks will inevitably affect China's financial markets. Previous studies have shown that GPR can affect the price dynamics of China's crude oil futures [24] and China's rare metals [25]. Furthermore, studies have also shown that GPR can affect the dynamics of China's stock market by using panel-GARCH models [26], and GPR can spill over to renewable energy stock markets in China [27]. However, they are failed to distinguish the differences of the impact of general GPR from categorical GPR (categorical GPR refers to the geopolitical action risk and the geopolitical threat risk.). As in the study of Caldara and Iacoviello [4], the geopolitical threats index (GPR_{Treat}) and the geopolitical acts index (GPR_{Act}) are proposed to capture different features of GPR, and current studies found that the impacts of GPR_{Treat} and GPR_{Act} on asset prices are different and ambiguous [4, 23–25]. Thus, it is necessary to fill this gap by investigate the performance of GPR_{Treat} and GPR_{Act} individually and provide evidence on the mechanism of GPR's impact on China's stock market.

From the perspective of the regional structure of China's OFDI, before 2017, China's OFDI was focused on developed countries such as Europe and the USA, and they were accounted for 9.6% of total OFDI in China in 2005, and 48.7% in 2017. At the same time, these countries also experienced several geopolitical events, such as the 9/11 attacks in the USA, the Gulf War, the Ukraine/Russia crisis, and the 2015 Paris terror attacks. After 2017, China's outbound investment returned to East Asia, and most of them are emerging economies. In 2019 and 2020, the proportion of China's OFDI in East Asia is 21.1% and 34.7%, respectively, both exceeding the investment share of Europe, the USA, and other regions. Meanwhile, the geopolitical turmoil in East Asia has also accelerated in recent years. The increasing conflict in the Syrian, the US–North Korea tensions over nuclear proliferation, the Qatar–Saudi Arabia proxy conflict, and most recently, the US–China tensions and the outbreak of COVID-19 have all increased the comlexity of GPR. It can be seen that even though the regional structure of China's outbound investment is constantly changing, the GPR is constantly posing a wide range of threats to the China stock market. Under such circumstances, related studies need to pay more attention to the effects of regional GPR and distinguish the differences from those of global ones.

During 2018 US–China tensions, China experienced huge fluctuations in their stock market, which caused huge losses for the investors. Such loss could have been avoided if the investors track the early warning signals from the changes of GPR. Thus, it is also important for investors to predict the volatility of China's stock returns using GPR.

In conclusion, the motivation among investors and policy-makers to explain and predict the volatility of China's stock returns using GPR is intuitive. However, the related topic is not a widely discussed issue, and it requires more attention. In this paper, we address the above issues by employing the GARCH-MIDAS model with different GPR indices, such as the categorical GPR indices as well as the regional GPR index from 18 different emerging economies, to distinguish the effects of categorical and regional GPR from those of general and global ones. We further employ the MCS test to evaluate the predictive potential of these GPR factors. To the best of our knowledge, we are among the first to analyze the heterogeneous effects of categorical and regional GPR factors on the China stock market volatility and also the first to evaluate the predictive ability of these factors.

The results in this paper provide some evidence for the mechanism of the GPR's impact on China's stock market. First, GPR positively influences the volatility of China's stock returns, and the effect is significant, which indicates that a higher GPR would lead to increased market volatility. With respect to the categorical GPR indices, we find that compared with GPR_{Act}, GPR_{Treat} generates a stronger and positive impact on the volatility in CSI 300, which indicates that in China, investors are more sensitive to geopolitical threats rather than geopolitical actions. In addition, the coefficient of GPRS is larger than that of GPR, indicating that market participants may be more sensitive to the serious GPR. Second, among 18 countries, the GPR in 10 countries and districts has a significant impact on the Chinese stock market. The $GPR_{Turkey,}$ $GPR_{Korea,}$ $GPR_{Indonesia}$, $GPR_{SaudiArabia}$, $GPR_{Colombia,}GPR_{Malaysia}$ and $GPR_{Philippines}$ significantly reduced the volatility in CSI 300, whereas the GPR_{Brazil}, GPR_{China}, and $GPR_{Venezuela}$ significantly increased the volatility in CSI 300. We provide some explanations of this heterogeneity in terms of geography, international investment, and petroleum economics. Third, in turns of the forecasting performance, the GPR_{Act} has the most information about future volatility in CSI 300, which provides the most accurate volatility forecast and the best economic performance.

We make the following contributions. First, we use the newly constructed GPR indices proposed by [4], which helps us capture the continuous fashion of GPR. In addition, the relationship between the volatility in CSI 300 and GPR factors is examined using the GARCH-MIDAS models, which fills up the gap that there is scant literature investigating GPR's impact on the Chinese stock market. Second, as indicated above, we employed the general GPR index, the categorical GPR indices, and the regional GPR indices in 18 emerging economies. Thus, our research adds the literature on the relationship between GPR and financial market movements by capturing a wider range of exogenous GPR. At the same time, we also discuss the heterogeneous influence of different regions and different categories of GPR on the volatility of China's stock market. Third, to the best of our knowledge, we are the first to investigate the out-of-sample prediction performance of the volatility in CSI 300 by employing the GARCH-MIDAS model with GPR information.

The balance of this paper unfolds as follows. Section 2 presents a brief literature review related to the topic. Section 3 introduces the research methodology. Section 4 discusses the data and the empirical results. Section 5 concludes this study.

2. Literature Review

As is known to all, historical events are reflected in asset prices [18]. The literature on the nexus between the volatility of stock market returns and GPR was pioneered by studies based on a specific type of GPR or individual geopolitical events (see [1, 28–33], among others). One of the most important GPR in the past literature is the risk of political uncertainty, which describes the risk of antigovernment demonstrations, riots, and assassinations [33]. Schwert [34] and Veronesi [35] proposed a theoretical model and found that increasing political instability can lead to increased stock market volatility. Erb et al. [36] found that the relationship between political risk and future stock returns is positive but weak. Bittlingmayer [37] used the data from the early 1920s and shows that political uncertainty has a positive impact on the volatility of stock returns. Voth [33] found that the increasing stock volatility can be partly explained by political uncertainty during the Great Depression period. Likewise, Brown et al. [38] argue that political stability contributes to the low volatility of consols during the Pax Britannica (1816–1913) period. Boutchkova et al. [39] found that there is a positive relationship between political uncertainty and stock volatility. Pástor and Veronesi [40] found that uncertainty also increases the volatility of stocks and makes them more correlated. Among these, the GPR is one of the major uncertainties in the world. Some studies focus on the risks of rare disasters. Kaplanski and Levy [28] found that aviation disasters have an event effect and can increase the implied volatility of the stock market. Berkman et al. [41] provide evidence that rare disaster risk can also affect the mean and volatility of stock market returns. Some studies have investigated the influence of the war, such as Frey and Kucher [42] and Choudhry [43]. Wolfers and Zitzewitz [30] find that changes in the probability of war can explain over 30% of the variation in the S&P between September 2002 and February 2003. Another strain of literature focuses on the risk of terrorist activity. Drakos [31] investigated the systematic effect of the overall terrorist activity on stock markets. Aslam and Kang [44] found that terrorist attacks have adversely impacted the Pakistani stock market.

While these past works make a preliminary investigation about the relationship between the GPR and the stock market, most of these studies are limited to a certain type of event, and it fails to describe the general characteristics of the influence of GPR on stock markets.

Based on the textual analysis method, Caldara and Iacoviello [4] were able to describe the general character of geopolitical events. They developed a news-based GPR index that includes not only terrorist attacks but also war risks, military threats, geopolitical uncertainties, and tensions, thus providing a real-time indicator for geopolitical risk. After the GPR index was proposed, there are a growing number of academic researchers who turned their interests to the relationship between GPR and the stock market. Some studies show that GPR can influence the volatility of stocks in a given industry, such as global defense companies [45], global travel and leisure companies [23], and rare metals companies [25]. Besides the impact of GPR has on the volatility of stocks in a given industry, some researchers turn their research interest to the general impact of the GPR on the stock price index [7, 8, 11, 26, 46] and the specific role of GPR in different countries [47]. Moreover, previous studies provided some evidence that GPR has an impact on alternative investment such as gold and crude oil [25, 48–50].

With only a few exceptions [7, 24, 48], however, the above studies are mainly focused on the relationship between GPR and the stock market returns; the relationship between GPR and volatility is understudied in the literature. Fornari and Mele [51] argue that financial volatility can significantly influence capital investment, consumption, and economic activities; thus, the reason behind these changes should have drawn further attention among academics and practitioners [52]. Furthermore, except for [24], previous studies mainly concentrate on the developed economies, and the case of emerging economies needs to receive more attention. More importantly, the studies concerning the relationship of stock volatility and GPR do not distinguish the differences between regional and global GPR. Since emerging economies are vulnerable to local and global GPR shocks [52], these differences are particularly important.

Among all the volatility models, the GARCH-MIDAS model is widely used in examining the low-frequency macroeconomic drivers behind the changes in financial volatility. The GARCH-MIDAS model was constructed by Engle et al. [53], and they found that the long-term component of stock volatility is directly driven by inflation and industrial production. After that, a growing number of researchers have used this method to investigate the macroeconomic drivers behind the changes in financial volatility [54–58].

In conclusion, while the above literature provides some insights for further investigations involving the relationship between GPR and the volatility of stock market returns, it lacks the following contributions. First, with respect to the early researches of GPR and stock market volatility, most of this literature is limited to a certain type of GPR of geopolitical events, and it fails to describe the general effects of geopolitical risks on stock markets. We address this by using the GPR indices calculated by Caldara and Iacoviello [4] to describe the general GPR. Since the GPR indices were calculated from various sources, they provide a much broader description of the features of GPR. In addition, these sets of GPR indices recently have been widely used in the current literature [6, 8, 23–27, 47–50, 52, 59–62]. Second, except [24], most studies focus on the developed countries, and the case of emerging economies needs more attention. We focus on the GPR influence on China, which is the largest emerging economy in the world. Third, with only a few exceptions [7, 24, 48], current studies mainly focus on the GPR's impact on the stock market returns, GPR's impact on the stock market volatility is understudied in literature. Against this backdrop, we focus on the volatility in CSI 300. The CSI 300 index is representative for China stock market because it is constructed by 300 large-capitalization stocks listed in either Shanghai or Shenzhen Stock Exchanges; these stocks are usually actively traded and their capitalization is accounted for about 70% of the total market capitalization. Thus, the CSI 300 index is one of the most representative indices of the Chinese stock market. Fourth, previous studies fail to investigate the different impacts of regional GPR from those of global ones. Thus, we use the global GPR index as well as the regional GPR index from 18 different emerging economies to distinguish the different effects of regional GPR.

3. Methodology

3.1. The GARCH-MIDAS Model. The conditional variance of the GARCH-MIDAS model is constructed by two parts: the short-run and the long-run components. The short-run components are a mean reverting GARCH (1, 1) like process, and the long-run components are constructed by realized volatility and extended by low-frequency variables [63]. This specific feature makes the GARCH-MIDAS model superior in explaining and forecasting the volatility in CSI 300 with GPR indices. Thus, we employed the GARCH-MIDAS model with realized volatility (RV) as our benchmark model and the GARCH-MIDAS model with RV and GPR indices as our extended models. Suppose the return of the CSI 300 is written as follows:

$$r_{it} = \mu + \sqrt{\tau_t g_{it}}\varepsilon_{it}, \quad \forall i = i, \ldots N_t, \tag{1}$$

$$\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0, 1), \tag{2}$$

where r_{it} refers to return in CSI 300 on day i in month t. The information set is $\Phi_{i-1,t}$, and μ is the conditional mean of returns up to day $i-1$. We set $E_{i-1t}(r_{it}) = \mu$ because the mean of daily returns in CSI 300 is usually very small; in our case, it is close to zero. The dynamics of the returns are usually determined by variance.

The $\sqrt{\tau_t g_{it}}$ refers to the variance component, and equation (1) is decomposed into two parts: a short-run component, g_{it}, and a long-run component, τ_t. Suppose g_{it} is following a GJR-GARCH (1, 1) process with mean reverting and unit variance, it can be defined as follows:

$$g_{i,t} = \left(\frac{1-\alpha-\gamma}{2-\beta}\right) + \left(\alpha + \gamma 1_{\{\varepsilon_{i-1,t<0}\}}\right)\frac{\varepsilon_{i-1,t}^2}{\tau_t} + \beta g_{i-1,t}. \tag{3}$$

As for the long-run component, τ_t is usually defined as a smoothed realized variance with an exogenous variable basing on a gently varying weight function. The expression is as follows:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k V_{t-k}, \tag{4}$$

where m is the intercept and θ refers to the slope, suggesting the weighted effects of lagged variables, V_t, on the long-run volatility in CSI 300. To make sure that the conditional variances are nonnegative, we use the following log transformation [64].

The following equation refers to the log transformation:

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\mathrm{RV}_{t-k}, \tag{5}$$

$$\mathrm{RV}_t = \sum_{i=1}^{N_t} r_{i,t}^2, \tag{6}$$

where RV is calculated by equation (6) and k is the size of the RV's rolling window. The weighting scheme φ_k used in equation (4) can be constructed by the unrestricted Beta function as follows [50, 53, 63]:

$$\varphi_k(\omega) = \frac{(k/K)^{\omega-1}}{\sum_{j=1}^{K} (j/K)^{\omega-1}}, \tag{7}$$

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K} (j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}}, \tag{8}$$

where the parameters ω_1, ω_2 are the decaying rate of the Beta function. Following Engle et al. [53], Su et al. [65], and Liu et al. [50], we set the constrained weighting scheme as $\omega_1 = 1$, and equation (8) can be updated as follows:

$$\varphi_k(1, \omega_2) = \frac{(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K} (1-j/K)^{\omega_2-1}}. \tag{9}$$

3.2. Extended Models with GPR Indices. To investigate the explaining and forecasting ability of GPR factors for volatility in CSI 300, we employ the GPR factors to equation (4), and we can get the GARCH-MIDAS-GPR model. We reconstructed the long-run component, $\log(\tau_t)$, as follows:

$$\log(\tau_t) = m + \theta_1 \sum_{k=1}^{K} \varphi_k(1, \omega_{2,1})\mathrm{RV}_{t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(1, \omega_{2,2})\mathrm{GPR}_{t-k}, \tag{10}$$

where the GPR is the global GPR index, the categorical GPR indices, and the regional GPR indices (the GPR index in China, Colombia, India, Indonesia, Israel, Korea, Malaysia, Mexico, the Philippines, Russia, Saudi Arabia, Thailand, South Africa, Turkey, Ukraine, Venezuela, and Brazil). To further investigate the explaining and forecast ability of serious GPR index, we define the GPRS as follows:

$$\mathrm{GPRS}_{t-k} = \mathrm{GPR}_{t-k} \times I(\mathrm{GPR}_{t-k} > \mathrm{GPR}^{\mathrm{mean}}). \tag{11}$$

4. Empirical Analysis

4.1. Data. We use CSI 300 Index to comprehensively investigate the general movements and trends of China's A-share markets. CSI 300 Index was created on April 8, 2005, and is the first stock price index that measures the overall performance of China's A-shares. The CSI 300 index is representative for China stock market because it constructed by 300 large-capitalization stocks listed in either Shanghai or Shenzhen Stock Exchanges; these are accounted for about 70% of the total market capitalization. We use its five-minute high-frequency data to calculate the daily returns and realized volatility. We use the global GPR index and the categorical GPR indices, the $\mathrm{GPR}_{\mathrm{Act}}$, $\mathrm{GPR}_{\mathrm{Treat}}$, $\mathrm{GPR}_{\mathrm{Narrow}}$, and $\mathrm{GPR}_{\mathrm{Broad}}$ index, as well as the GPR indices from 18 emerging economies calculated by [4], to show the GPR in different forms and of each country. Following Hasan et al. [52] and Caldara and Iacoviello [4], the GPR index from the USA can be the proxy for global GPR. The sample period of this paper ranged from September 2011 to July 2020. The CSI 300 index data were obtained from the Wind database, and the monthly data of the GPR indices were retrieved from https://www.matteoiacoviello.com/gpr.htm. According to [4], the GPR indices are normalized to average a value of 100 in the 2000–2009 decade, so the GPR indices represent the frequency with which rising GPR terms were mentioned compared to the 2000s. For instance, when GPR equals 200, it indicates that newspaper mentions of rising GPR in that month were twice as frequent as they were during the 2000s.

Before we formally analyze the explaining ability and the predictive potential of GPR indices for China's stock market, we examine the descriptive statistics of returns in CSI 300, volatility, and GPR indices first. According to Table 1, the skewness and kurtosis values indicate that the returns in CSI 300 are negatively skewed and fat-tailed, the volatility in CSI 300 is positively skewed and fat-tailed and so as most of the GPR indices. In addition, the Jarque–Bera test statistics also indicate that these variables do not follow the normal distribution. Among the selected 18 emerging economies, based on the average value of the GPR index, the countries with the top six geopolitical risks are Ukraine, Turkey, South Korea, Mexico, Russia, and China. Particularly, the average value of the GPR index of China is 119.62, and its standard error is 33.55, which indicates that China's GPR is relatively weak and stable.

Figure 1 shows the changes of RV from CSI 300 and the GPR index from September 7, 2011, to July 8, 2020. It can be seen from Figure 1 that during the Syria war escalation, ISIS escalation, and US–China tensions, the CSI 300 exhibits dramatic turbulence, implying obvious comovements there. As shown in Figure 1, the $\mathrm{GPR}_{\mathrm{Act}}$ index only increases when particular events took place, while the $\mathrm{GPR}_{\mathrm{Treat}}$ index increases around major geopolitical events and continues to grow for a long time after the events. As can be seen from Figure 1, the $\mathrm{GPR}_{\mathrm{Treat}}$ index is more consistent with the movements of stock volatility than the $\mathrm{GPR}_{\mathrm{Act}}$ index.

In terms of the GPR trend from different countries, the GPR from Brazil, China, Mexico, India, and Ukraine show a

Table 1: Descriptive statistics.

	Mean	Max	Min	SD	Skew	Kurt	JB	Obs
RTN	0.000	0.065	−0.092	0.015	−0.729	8.601	2972.829	2130
RV	0.000	0.005	0.000	0.000	8.144	92.310	731437.300	2130
GPR_{Narrow}	126.246	401.311	43.980	63.751	1.148	4.670	715.039	107
GPR_{Treat}	130.838	419.622	45.227	66.682	1.158	4.656	719.681	107
GPR_{Act}	64.300	271.608	16.152	37.190	2.211	11.179	385.430	107
GPR_{Broad}	103.502	293.096	45.209	38.130	1.519	7.451	129.453	107
GPR	119.499	380.102	41.986	58.990	1.264	5.415	54.472	107
GPR_{China}	119.619	253.399	65.509	33.552	1.058	4.235	532.721	107
$GPR_{Colombia}$	63.909	162.157	22.782	26.236	0.902	4.365	454.338	107
GPR_{India}	84.124	156.611	54.925	17.173	1.086	5.500	973.259	107
$GPR_{Indonesia}$	55.773	134.635	21.748	19.104	1.302	5.875	1334.829	107
GPR_{Israel}	82.782	135.771	48.765	16.980	0.599	3.540	153.345	107
GPR_{Korea}	125.269	274.424	51.584	43.653	1.253	5.111	952.931	107
$GPR_{Malaysia}$	91.564	271.070	22.628	38.861	1.737	7.933	3230.115	107
GPR_{Mexico}	123.107	215.508	72.698	24.778	0.764	4.044	304.100	107
$GPR_{Philippines}$	114.263	213.645	51.765	37.344	0.488	2.691	93.092	107
GPR_{Russia}	121.347	220.077	61.947	28.958	0.588	3.743	171.803	107
$GPR_{Saudi\ Arabia}$	109.323	196.283	53.280	28.159	0.187	3.096	13.171	107
$GPR_{South\ Africa}$	79.579	246.356	36.627	32.625	1.973	9.621	5271.682	107
$GPR_{Thailand}$	89.699	266.187	35.755	41.129	1.490	5.768	1467.735	107
GPR_{Turkey}	140.583	234.281	76.793	34.776	0.405	2.717	65.246	107
$GPR_{Ukraine}$	172.968	310.174	22.178	78.422	−0.465	2.168	138.149	107
$GPR_{Venezuela}$	110.889	232.615	46.746	33.769	1.100	5.026	793.796	107
$GPR_{Argentina}$	97.703	250.991	36.402	40.373	1.028	4.071	23.952	107
GPR_{Brazil}	110.932	212.761	43.023	33.564	0.920	4.074	20.222	107

Notes: RTN is the daily returns in CSI 300. RV is the realized variance. GPR is the geopolitical risk index. GPRS is a serious geopolitical risk index calculated by equation (11). GPR_{Treat} is the geopolitical threat risk index. GPR_{Action} is the geopolitical act index.GPR_{Broad} and GPR_{Narrow} are the broad and narrow definitions of GPR, respectively. GPR_{China}, $GPR_{Colombia}$,GPR_{China}, GPR_{India}, $GPR_{Indonesia}$, GPR_{Israel}, GPR_{Korea}, $GPR_{Malaysia}$, GPR_{Mexico}, $GPR_{Philippines}$, GPR_{Russia}, $GPR_{Saudi\ Arabia}$, $GPR_{Thailand}$, $GPR_{South\ Africa}$, GPR_{Turkey}, $GPR_{Ukraine}$, $GPR_{Venezuela}$, and GPR_{Brazil} are the GPR index in the mainland of China, Colombia, India, Indonesia, Israel, Korea, Malaysia, Mexico, the Philippines, Russia, Saudi Arabia, Thailand, South Africa, Turkey, Ukraine, Venezuela, and Brazil, respectively. For the sake of numerical stability, we multiply the log returns and the realized volatility by 100. JB is the Jarque–Bera test statistics. Obs is the sample size.

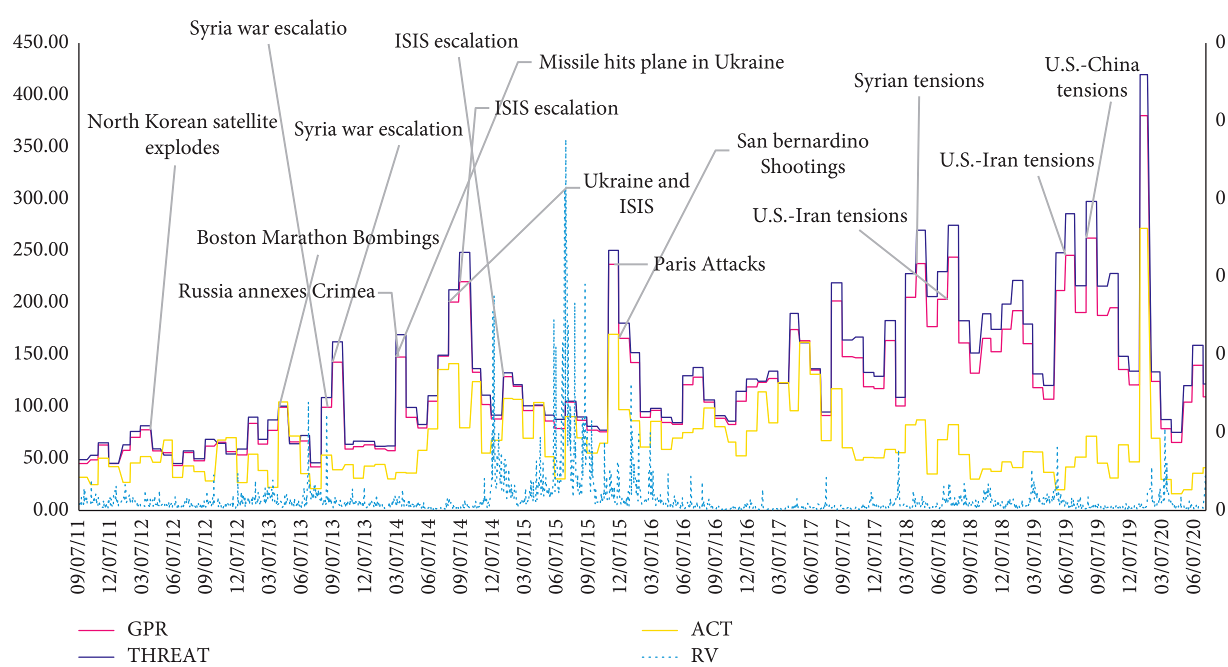

Figure 1: The trends of stock volatility and the categorical GPR index.

yearly increasing trend. In particular, after the Ukraine crisis in 2013, the GPR rose sharply and has remained at a high level ever since. The GPR of Saudi Arabia, Turkey, Colombia, North Korea, Indonesia, and Russia showed an initial rising and then falling trend. In particular, the GPR of Malaysia, the Philippines, Venezuela, and Iran showed an obvious trend of declining in the recent year. Argentina, South Africa, and Thailand showed the trend of periodic fluctuation in GPR.

In terms of geographical location, GPR changes among countries show significant geographical location similarities. In the 18 emerging economies, Brazil, Venezuela, Colombia, and Argentina are located in South America, so Figure 2 shows that these four countries are similar to some extent. The changes in the GPR in these four countries are characteristic of periodic fluctuation. Particularly, Brazil, Venezuela, and Colombia as neighboring countries; thus, there are more significant similarities among these three countries. Russia, Ukraine, China, Turkey, Saudi Arabia, India, North Korea, Indonesia, and Malaysia are located in Asia, so the GPR of these countries are also similar to a certain extent. In particular, neighboring countries such as Malaysia, Indonesia, and Thailand; India and China; and Ukraine and Russia all show more obvious similarities.

4.2. In-Sample Estimation. Following [50, 53], we set the lag length K of long-run RVs equal to 22 and the lag length K of monthly GPR factors equal to 24. The parameters of the benchmark and extended GARCH-MIDAS model are obtained using the maximum likelihood estimation (MLE) method. The results are shown in Tables 2–6. As shown in these tables, the log-likelihood function value (LLF), the Bayesian information criterion value (BIC), and the variance ratio (VR) are shown last three columns. Note that the extended GARCH-MIDAS models with geopolitical risk factors employ return data for the 2013:M9 to 2020:M7 period, while the benchmark GARCH-MIDAS model employs data from 2011:M9 onwards. Hence the benchmark GARCH-MIDAS model cannot be compared to the extended GARCH-MIDAS models in terms of log-likelihood or Bayesian information criterion (BIC). However, similar to Conrad and Kleen [66], we should be able to compare its prediction performance in the next section.

As shown in equation (3), if the estimated parameters α, γ, and β hold for $(\alpha+\gamma)/(2+\beta)<1$, then the model is stable. In Tables 2–6, for all the benchmark and extended GARCH-MIDAS models, the biggest value of $(\alpha+\gamma)/(2+\beta)$ is 0.9995 in the GARCH-MIDAS-GPR_{Broad} model. Thus, both benchmark and extended GARCH-MIDAS models are stable. The γ parameter is insignificant and indicating that there is no significant evidence for the asymmetry effect.

The parameters θ_1 and θ_2 in equation (9) depict the impact of RV and GPR factors on long-term stock volatility. Specifically, the positive value of θ_1 and θ_2 means a high-level RV and GPR would increase the volatility in CSI 300. The parameters $\omega_{2,1}$ and $\omega_{2,2}$ refer to the optimal estimated coefficients for the BETA function in equations (7)–(9). We can observe the impact of monthly RV and GPR factors on the long-term component of volatility in CSI 300.

In the following section, Tables 2 and 3 present the heterogeneous effects of different categorical GPR indices, and Tables 4–6 present the heterogeneous effects of GPR indices from different countries.

4.2.1. The Heterogeneous Effects of Different Categorical GPR Indices on the Volatility in CSI 300. θ_2 are 0.007 and 0.012 for GPR and GPRS and significant under 5% and 1% levels, respectively. Indicating that both GPR and GPRS can influence the China's stock market participants by making them have different expectations of the market as well as different trading activity with a different direction, which leads to increased market volatility. Especially, the coefficient of GPRS is larger than that of GPR, indicating that market participants are more sensitive to the serious GPR.

Second, by investigating the categorical GPR indices, the estimated parameters of GPR_{Treat}, GPR_{Broad}, and GPR_{Narrow} are 0.05, 0.046, and 0.029, respectively, and significant, whereas the coefficient of GPR_{Act} is 0.04 and insignificant. In addition, the coefficient of GPR_{Treat} is larger than that of GPR_{Act}, which indicates that in China's stock market, investors are more sensitive to escalating geopolitical threats rather than geopolitical actions. Furthermore, from the perspective of investors' expectations, the actual geopolitical events are more helpful for investors to form a consistent expectation than geopolitical threats with a higher degree of uncertainty. Thus, this is also intuitive to show that the coefficient of GPR_{Treat} is larger than that of GPR_{Act}.

It is interesting to find that the impact of GPR_{Act} is insignificant. GPR_{Act} represents the realization of geopolitical actions, while GPR_{Treat} captures broader terms of geopolitical threats. As shown in Figure 1, the GPR_{Act} index only increases when particular events took place, while the GPR_{Treat} index increases around major geopolitical events and continues to grow for a long time after the events. Thus, it is reasonable that GPR_{Treat} has more profound influences on the long-term volatility of China's stock market. This pattern can also be observed by the impact of GPR_{Act} has on various financial assets such as stock returns [4] and WTI volatility [59].

4.2.2. The Heterogeneous Effects of GPR Indices from Different Countries on the Volatility in CSI 300. First, among 18 countries and districts, the GPR in 11 countries has a significant influence on the Chinese stock market. Specifically, the GPR_{Turkey}, GPR_{Korea}, GPR_{Brazil}, GPR_{China}, $GPR_{Indonesia}$, $GPR_{Saudi\ Arabia}$, $GPR_{Colombia}$, $GPR_{Venezuela}$, $GPR_{Malaysia}$, $GPR_{Philippines}$, and $GPR_{Hong\ Kong\ of\ China}$ have significantly influenced the stock volatility, whereas the GPR_{Mexico}, $GPR_{Argentina}$, GPR_{Russia}, GPR_{India}, $GPR_{South\ Africa}$, $GPR_{Thailand}$, GPR_{Israel}, and $GPR_{Ukraine}$ have no significant influence on the volatility in CSI 300 returns.

Second, among the countries that have a significant impact on the stock volatility, the coefficients of GPR_{Turkey},GPR_{Korea}, $GPR_{Indonesia}$, $GPR_{Saudi\ Arabia}$, $GPR_{Colombia}$, $GPR_{Malaysia}$, and $GPR_{Philippines}$ are −0.017, −0.010, −0.031, −0.011, −0.024, −0.010, and −0.009, respectively. This shows that the GPR in these countries can

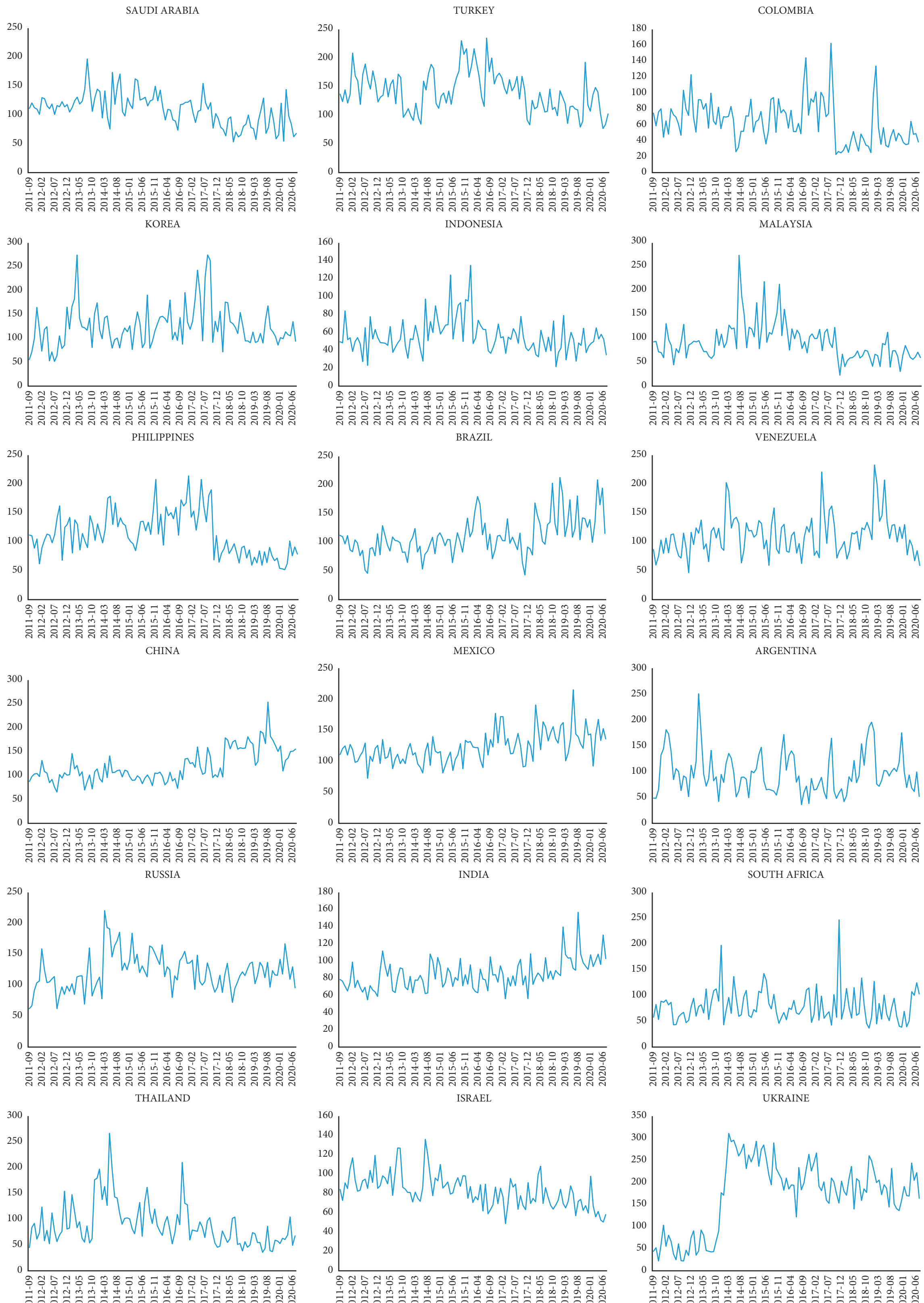

Figure 2: The trends of GPR indices from different countries.

Table 2: The heterogeneous effects of different categorical GPR indices on the volatility in CSI 300.

	RV	GPR	GPRS
μ	0.062	0.063*	0.062*
	0.039	0.037	0.037
α	0.096***	0.088***	0.088***
	0.017	0.016	0.016
β	0.861***	0.873***	0.865***
	0.020	0.023	0.025
γ	0.014	0.004	0.007
	0.018	0.019	0.020
m	−0.875***	−2.062***	−1.406***
	0.287	0.542	0.296
θ_1	1.448***	1.627***	1.571***
	0.207	0.209	0.191
$\omega_{2,1}$	8.268***	7.812***	8.407***
	2.654	2.472	2.575
θ_2		0.007**	0.012***
		0.003	0.004
$\omega_{2,2}$		8.787*	4.483**
		4.931	2.174
LLH	−2701.110	−2707.680	−2706.440
BIC	5460.151	5482.121	5479.640
VR	54.474	60.563	62.963

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The asterisks indicate statistical significance at the 1% (***), 5% (**), or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $\mathrm{VR}(X) = \mathrm{var}(\log(\tau_M^X))/\mathrm{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

Table 3: The heterogeneous effects of different categorical GPR indices on the volatility in CSI 300.

	GPR_{Treat}	GPR_{Act}	GPR_{Broad}	GPR_{Narrow}
μ	0.062*	0.063*	0.060*	0.058
	0.037	0.037	0.035	0.036
α	0.089***	0.093***	0.080***	0.081***
	0.016	0.015	0.011	0.012
β	0.873***	0.884***	0.929***	0.923***
	0.024	0.021	0.009	0.009
γ	0.001	−0.002	−0.019	−0.010
	0.019	0.019	0.015	0.016
m	−1.811***	−1.165***	−2.303*	−0.225
	0.465	0.359	1.261	1.568
θ_1	1.600***	1.462***	−0.832	−1.478
	0.207	0.229	1.440	1.753
$\omega_{2,1}$	8.071***	6.979**	4.278	2.844
	2.570	2.731	6.861	2.947
θ_2	0.005**	0.004	0.046**	0.029***
	0.002	0.003	0.020	0.010
$\omega_{2,2}$	15.286	21.334	1.463	1.000*
	9.536	25.548	0.932	0.526
LLH	−2707.360	−2711.330	−2708.350	−2710.370
BIC	5481.492	5489.425	5483.477	5487.510
VR	59.237	52.476	134.277	230.420

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The asterisks indicate statistical significance at the 1% (***), 5% (**), or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $\mathrm{VR}(X) = \mathrm{var}(\log(\tau_M^X))/\mathrm{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

significantly reduce the volatility in China's stock markets. Among these countries, only Colombia is located in South American; the rest are all located in Asia. Turkey and Saudi Arabia are all located in the Middle East region and have similar geographic characteristics. Saudi Arabia has the world's largest oil reserves and production and is one of China's major energy importers. Previous literature shows that GPR can have a positive impact on crude oil prices [59]. As mentioned in [67], China's dependence on imported oil keeps increasing since 2012, and in 2013, China was announced by the US Energy Information Administration (EIA) that it had become the largest net importer of crude oil among the world's economies. Demirer et al. [61] found that the influences of GPRs are different across the oil markets, and furthermore, Ozcelebi and Tokmakcioglu [68] discussed the influences of the GPR on oil futures volatility for several emerging economies and found that the GPR actually reduces oil price volatility. In addition, several pieces of literature have shown that there is a spillover effect between oil and the stock market [67, 69–71]. Thus, the GPR in Saudi Arabia may reduce the stock volatility in China by reducing its oil price volatility. Since Turkey is the neighboring country of Saudi Arabia, and Mansour-Ichrakieh and Zeaiter [47] show that Saudi Arabia seems to play an important role in the Turkish financial environment; it can be seen in Figure 2 that the GPR index in Turkey and Saudi Arabia are similar in the changing trend. Therefore, it is reasonable their GPR has the same impact on China's stock market.

Up to 2020, China was Colombia's second-largest importer and exporter. As can be seen from Figure 3, the abnormal increase in the volatility of China's stock market mostly occurred around the time when Colombia launched an antidumping investigation against China. Therefore, Colombia mainly influenced China's stock market through the trading activities between the two countries.

As can be seen from Figure 4, Colombia's trade sanctions against China tend to launch at a time when its GPR is low, which leads to the sharp decline of China's exports to Colombia. When the GPR is high, China's exports to Colombia are relatively stable. Figures 3 and 4 show that the negative relationship between Columbia GPR and the Chinese stock market volatility may be due to the changes in trade between the two countries. When Columbia's GPR is low, the trade sanctions on China from Columbia are more frequent, and the Chinese stock market is more volatile.

Korea, Indonesia, Malaysia, and the Philippines are China's neighboring countries, and they share geographic similarities. Gupta et al. [72] found that GPR has a negative impact on trade flows. Kim et al. [73] found that when North Korea's risk is increasing, foreign investors will reduce the value of their Korean portfolios. Ramiah and Graham [74] also show that domestic terrorist attack has negative impacts on the Jakarta Stock Exchange activities. Thus, we argue that when GPR rises in these four countries, foreign investment will flow into a geographically similar and financially stable market, in our case, China. As Figure 5 shows below, there is an obvious correlation between GPR in these four countries and the amount of Chinese foreign investment. Li et al. [75] found that foreign investment can stabilize the stock market and reduce the stock market volatility. So, we argue that

Table 4: The heterogeneous effects of GPR indices from Turkey, Mexico, Korea, Russia, India, China, and Brazil on the volatility in CSI 300.

	GPR_{Turkey}	GPR_{India}	GPR_{Korea}	$GPR_{Thailand}$	GPR_{Israel}	GPR_{China}	GPR_{Brazil}
μ	0.057	0.062	0.060	0.061	0.061	0.060	0.062
	0.039	0.039	0.039	0.039	0.038	0.039	0.038
α	0.079***	0.091***	0.084***	0.096***	0.092***	0.084***	0.096***
	0.019	0.017	0.017	0.017	0.018	0.018	0.018
β	0.844***	0.871***	0.842***	0.861***	0.868***	0.872***	0.877***
	0.027	0.020	0.027	0.021	0.020	0.022	0.019
γ	0.028	0.009	0.026	0.016	0.011	0.012	0.006
	0.019	0.017	0.019	0.018	0.018	0.017	0.018
m	1.536*	−2.347	0.599	−1.231	−3.281**	−2.338***	−2.724**
	0.790	1.436	0.635	1.025	1.570	0.652	1.192
θ_1	1.318***	1.555***	1.225***	1.416***	1.457***	1.539***	1.658***
	0.267	0.266	0.202	0.266	0.210	0.247	0.264
$\omega_{2,1}$	9.027***	7.361***	12.947***	8.344***	7.703***	7.410***	6.640***
	3.017	2.521	3.608	2.723	2.763	2.507	2.381
θ_2	−0.017***	0.011	-0.010***	0.003	0.028	0.011**	0.016*
	0.005	0.010	0.004	0.009	0.019	0.005	0.009
$\omega_{2,2}$	1.144	1.001	8.096	5.155	1.790	1.005	1.000
	0.726	2.277	5.380	22.005	2.866	1.435	0.873
LLH	−2705.820	−2712.870	−2708.500	−2713.990	−2711.160	−2710.230	−2713.710
BIC	5478.413	5492.510	5483.763	5494.748	5489.081	5487.229	5494.185
VR	9.009	51.345	66.273	55.128	56.169	57.044	52.772

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The asterisks indicate statistical significance at the 1% (***), 5% (**), or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $\mathrm{VR}(\mathrm{X}) = \mathrm{var}(\log(\tau_{\mathrm{M}}^{X}))/\mathrm{var}(\log(\sigma_{\mathrm{M}}^{X}))$ is calculated on monthly aggregates.

Table 5: The heterogeneous effects of GPRs indices from Indonesia, Saudi Arabia, South Africa, Colombia, and Venezuela on the volatility in CSI 300.

	$GPR_{Indonesia}$	$GPR_{Saudi\ Arabia}$	$GPR_{South\ Africa}$	$GPR_{Colombia}$	$GPR_{Venezuela}$
μ	0.062	0.060	0.061	0.062	0.059
	0.039	0.039	0.039	0.039	0.038
α	0.088***	0.090***	0.096***	0.082***	0.089***
	0.018	0.017	0.017	0.019	0.018
β	0.848***	0.865***	0.864***	0.850***	0.862***
	0.024	0.021	0.020	0.026	0.022
γ	0.017	0.012	0.012	0.016	0.020
	0.019	0.018	0.018	0.019	0.019
m	0.568	0.185	−0.107	0.601	−4.259***
	0.595	0.684	1.528	0.507	1.304
θ_1	1.669***	1.588***	1.472***	1.369***	1.309***
	0.376	0.237	0.252	0.191	0.252
$\omega_{2,1}$	6.729***	7.722***	7.865***	9.572***	8.033**
	2.299	2.445	2.851	2.684	3.132
θ_2	−0.031***	−0.011*	−0.009	−0.024***	0.031***
	0.012	0.007	0.021	0.007	0.012
$\omega_{2,2}$	1.000	1.001	1.000	3.839*	1.001**
	0.835	1.324	1.494	1.965	0.415
LLH	−2708.120	−2712.110	−2714.510	−2703.710	−2708.920
BIC	5483.004	5490.995	5495.783	5474.199	5484.616
VR	63.808	54.840	50.230	69.107	60.860

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The asterisks indicate statistical significance at the 1% (***), 5% (**), or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $\mathrm{VR}(X) = \mathrm{var}(\log(\tau_{M}^{X}))/\mathrm{var}(\log(\sigma_{M}^{X}))$ is calculated on monthly aggregates.

when the GPR in Korea, Indonesia, Malaysia, and the Philippines is increased, the foreign investment in these countries would flow into a geographic similar country, such as China, and reduce their stock market volatility.

The coefficients of GPR_{Brazil}, $GPR_{Venezuela}$, and GPR_{China} are 0.016, 0.031, and 0.011, respectively, and significant. This indicates that GPR in these countries can increase the volatility in China's market. Brazil is one of the BRICS

Table 6: The heterogeneous effects of GPRs indices from Argentina Thailand, Israel, Malaysia, the Philippines, and Ukraine on the volatility in CSI 300.

	$GPR_{Argentina}$	$GPR_{Thailand}$	GPR_{Israel}	$GPR_{Malaysia}$	$GPR_{Philippines}$	$GPR_{Ukraine}$
μ	0.060	0.062	0.061	0.062	0.064*	0.061
	0.040	0.038	0.039	0.039	0.037	0.039
α	0.090***	0.095***	0.095***	0.092***	0.082***	0.099***
	0.017	0.017	0.016	0.018	0.017	0.018
β	0.855***	0.859***	0.859***	0.849***	0.845***	0.859***
	0.022	0.020	0.023	0.023	0.027	0.020
γ	0.021	0.015	0.015	0.015	0.017	0.016
	0.018	0.018	0.020	0.019	0.019	0.019
m	−1.432**	−0.586*	−1.417	−0.163	0.051	−1.256**
	0.641	0.330	0.998	0.406	0.307	0.520
θ_1	1.397***	1.471***	1.387***	1.667***	1.466***	1.424***
	0.195	0.205	0.260	0.272	0.174	0.244
$\omega_{2,1}$	10.012***	8.384***	8.378***	7.486***	8.492***	8.010***
	3.169	2.706	2.980	2.142	2.565	2.648
θ_2	0.006	−0.004	0.007	−0.010**	−0.009***	0.002
	0.006	0.002	0.014	0.005	0.002	0.003
$\omega_{2,2}$	5.676	100.278	6.725	1.000	58.051	7.214
	6.837	774.159	19.001	1.017	45.552	15.420
LLH	−2713.400	−2711.380	−2713.780	−2710.540	−2699.520	−2713.490
BIC	5493.559	5489.529	5494.339	5487.857	5465.814	5493.750
VR	57.974	56.176	56.351	59.923	69.568	57.538

Notes: The numbers in parentheses are the standard errors of the estimated parameters. The asterisks indicate statistical significance at the 1% (***), 5% (**), or 10% (*) level. Log_Lik is the logarithm maximum likelihood function value. BIC is the Bayesian information criterion. The variance ratio $VR(X) = \text{var}(\log(\tau_M^X))/\text{var}(\log(\sigma_M^X))$ is calculated on monthly aggregates.

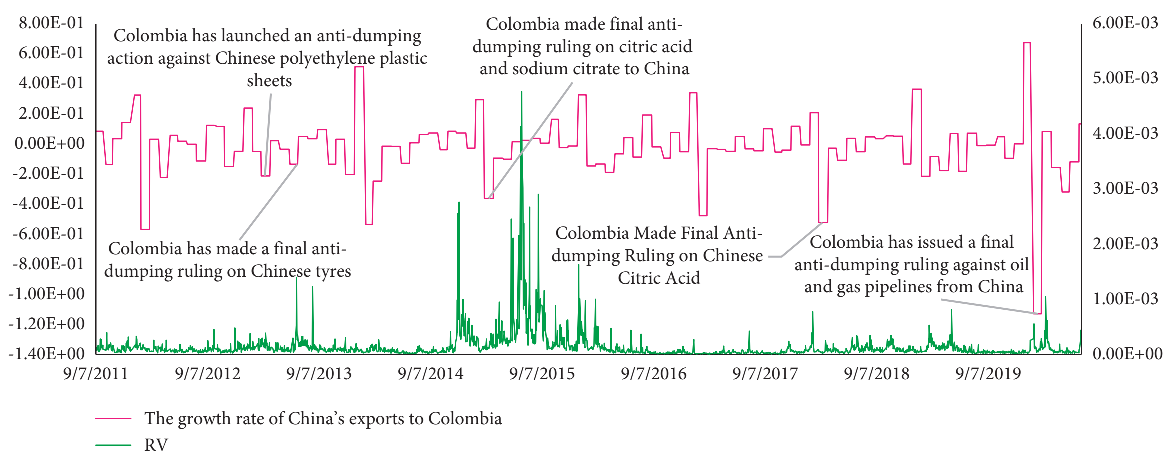

Figure 3: The trend of China's stock market volatility and the growth rate of China's exports to Colombia.

countries. Bhuyan et al. [76] found that the volatility of China is affected by BRICS countries overnight returns; especially, China's stock market volatility is negatively correlated with Brazil's overnight returns. Furthermore, Bouras et al. [26] found out that the GPR is negatively correlated with Brazil stock market returns. Thus, consistent with previous findings above, we argue that the increased GPR in Brazil may decrease stock market returns in Brazil and then increased the stock market volatility in China. Venezuela and Brazil are neighboring countries and are both located in South America, and it can be seen in Figure 6 that their similar impacts on China stock market may be shared with its geographical similarity.

As for China, it is reasonable that the rising domestic GPR would divergent the expectations of the investors and increase the volatility of China's stock market since the GPR would cause uncertainty to the economic and financial condition in the country.

4.3. Out-of-Sample Evaluation. The above analysis shows that GPR has significant influences on volatility in CSI 300. Now we further discuss the prediction performance of geopolitical risk. It should be noted that this part only discusses the prediction performance of global overall GPR on volatility in CSI 300. Bouras et al. [26] show that

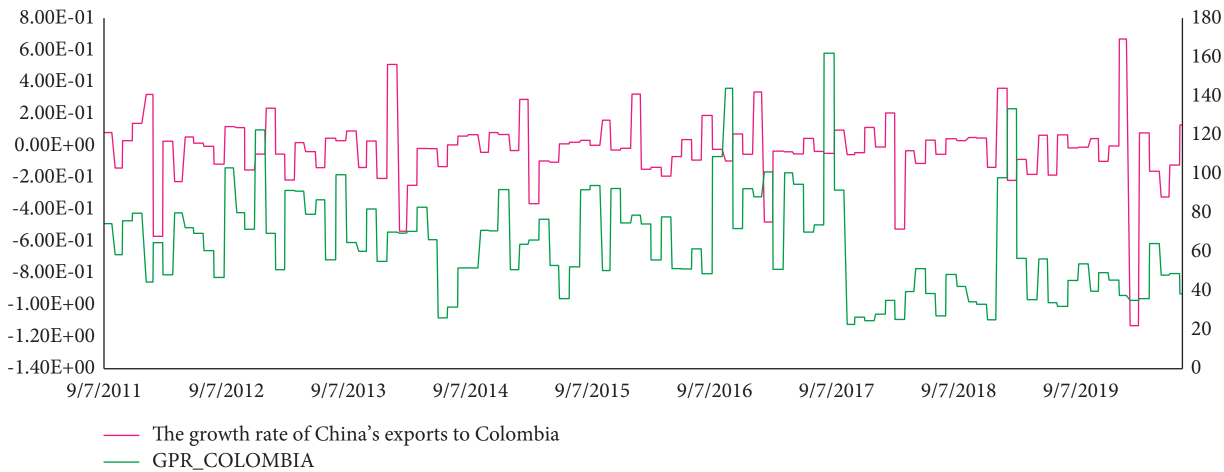

Figure 4: The trend of the growth rate of China's exports to Colombia and the GPR index in Colombia.

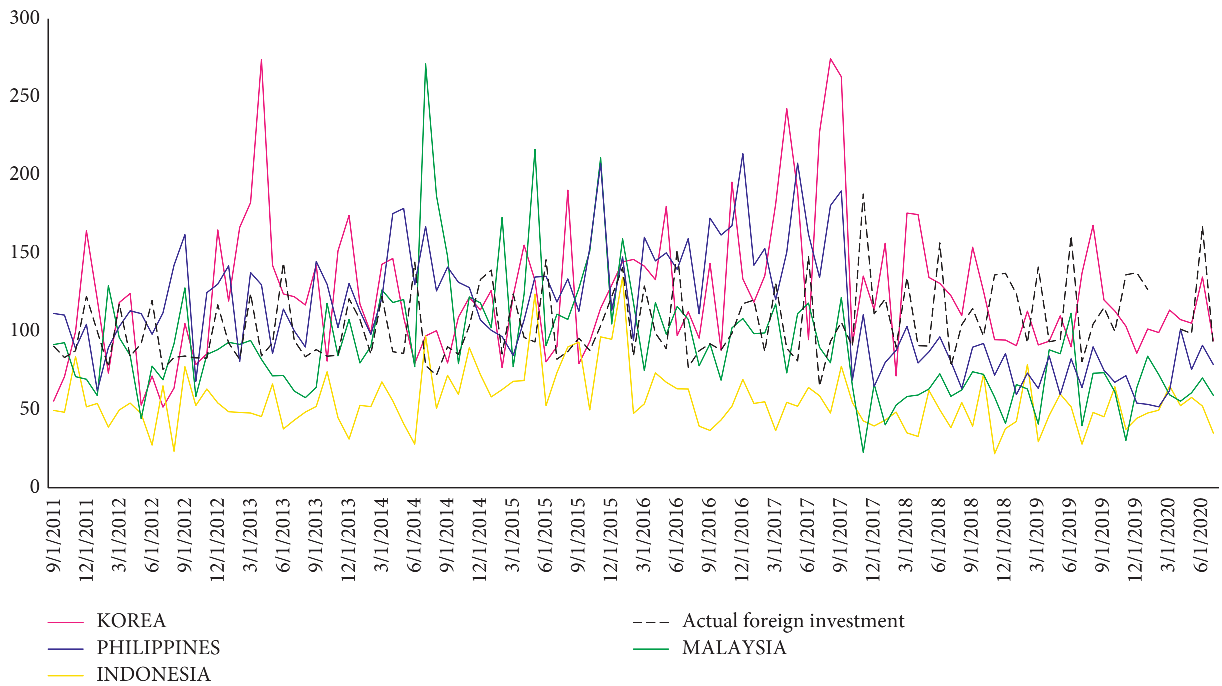

Figure 5: The trend of GPR in Korea, Indonesia, Malaysia, and the Philippines and the actual foreign investment (RMB).

the country-specific GPR's impact on stock market volatility is insignificant, whereas a broader measure of global GPR's impact is both economically and statistically stronger. It highlights the dominant role of global GPR when influencing the stock market. GPR in a given region usually only captures specific information in that specific region, while China is the world's second-largest economy, and its economic development is related to the general condition of the whole world. Therefore, it is of more economic significance to consider the prediction performance of global GPR rather than focus on a single country or region.

As for predicting the future volatility in CSI 300, we use the rolling window method. Specifically, the in-sample estimation period is from September 7, 2011, to January 2, 2019, and the corresponding out-of-sample forecasting period is from January 3, 2019, to July 8, 2020. To ensure that the sample size used for estimation is constant, and to keep the forecasts never overlap, we roll the estimation period forward by adding a new observation and dropping the very first observation. In addition, previous studies show that different lags of RV (RV_{t-k}) may lead to different accuracy; when predicting the value of the volatility, we follow the study of Engle et al. [50, 53], by employing the monthly,

Figure 6: The trend of GPR in Brazil and Venezuela.

biannual, and quarterly RV in the GARCH-MIDAS models (with lag length K of long-run RVs equals 22, 44, and 66, respectively). Under this solution, we also use the monthly, bimonthly, and quarterly RV in equations (5) and (9) for a robustness check, to investigate whether the extended GARCH-MIDAS model with GPR factors could robustly yield a more accurate forecast with different lags of RV. Following Mei et al. [62], we forecast the short-term (one-day-ahead) stock volatility as well as the longer-term (one-week-ahead and one-month-ahead) stock volatility.

4.3.1. The Forecast Performance of Different Categorical GPR Indices. To compare the predictive performance of the benchmark GARCH-MIDAS models and their extensions with GPR indices, we use the MCS test with the mean squared forecast error (MSFE) and the mean absolute forecast error (MAFE) as the loss functions to be our evaluation criteria. These loss functions are defined as follows:

$$\begin{aligned} \text{MSFE} &= M^{-1}\sum_{t=1}^{M}\left(y_t - \hat{y}_t\right)^2, \\ \text{MAFE} &= M^{-1}\sum_{t=1}^{M}\left|y_t - \hat{y}_t\right|, \end{aligned} \tag{12}$$

where y_t is the actual daily volatility in CSI 300, and it is calculated by the squared intraday returns on day t, whereas $\hat{y}_t$ is the volatility forecasts calculated from the benchmark GARCH-MIDAS models and its extensions, and M is the number of forecasts.

We use the MCS test to investigate the predictive potential of GPR factors. The p values of loss functions in the MCS test results are the main criteria when identifying the best performance models. The p values usually have a specific threshold, and when a model's p value is larger than the threshold, the corresponding model is supposed to have the best forecast performance compared with other models. For the exact value of such a specific threshold in the MCS test, there is no consensus in previous literature. Tian and

Table 7: MCS test with monthly RVs.

	TR		$T_{\max}$	
	SE	AE	SE	AE
One-day-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	0.000	0.000	0.000	0.000
GPR_{Act}	**1.000**	**1.000**	**1.000**	**1.000**
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-week-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	0.000	0.000	**1.000**	0.000
GPR_{Act}	**1.000**	**1.000**	**0.821**	**1.000**
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-month-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	0.000	0.000	**1.000**	**0.517**
GPR_{Act}	**1.000**	**1.000**	**0.630**	0.000
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	**0.863**	0.000
RV	**0.685**	**0.616**	0.000	0.000

Note. We use bold number stands for p values of the model that is greater than 0.25. The p value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error, and MAFE refers to the mean absolute forecast error. The lags of the RV are set to 22.

Table 8: Economic values of each model.

Models	$\gamma = -0.8$ R	$\gamma = -0.5$ R	$\gamma = -0.1$ R
GPR	1.415	2.259	11.268
GPRS	1.386	2.213	11.037
GPR_{Treat}	1.381	2.206	11.002
GPR_{Act}	12.293	19.665	98.298
GPR_{Broad}	1.323	2.113	10.536
GPR_{Narrow}	1.485	2.372	11.834
RV	1.075	2.037	7.154

Notes: This table reports the portfolio return (R) in percentage for a mean-variance investor who allocates assets between CSI 300 and risk-free bills using various volatility forecasts. We considered the values of the investor's risk aversion coefficient (γ) to be −0.8, −0.5, and −0.1. The portfolio return (R) is equal to $(w_t^* \hat{r}_t + r_{t,f})$.

Table 9: MCS test with bimonthly RVs.

	TR		T max	
	SE	AE	SE	AE
One-day-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	0.012	0.230	0.000	0.000
GPR_{Act}	**1.000**	**1.000**	**1.000**	**1.000**
GPR_{Broad}	**0.523**	0.000	**0.456**	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-week-ahead forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	**0.430**	**0.620**	**1.000**	0.000
GPR_{Act}	**1.000**	**0.877**	**1.000**	**1.000**
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-month-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	**1.000**	**0.783**	**1.000**	**0.517**
GPR_{Act}	**1.000**	**1.000**	**0.630**	0.000
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	**0.453**	0.000
RV	**0.483**	**0.315**	0.000	0.000

Note. We use bold number stands for p values of the model that is greater than 0.25. The p value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error, and MAFE refers to the mean absolute forecast error. The lags of the RV are set to 44. The bold values stand for p values of the model that is larger than 0.25.

Table 10: MCS test with quarterly RVs.

	TR		T max	
	SE	AE	SE	AE
One-day-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	**0.520**	**0.351**	0.204	**0.316**
GPR_{Act}	**1.000**	**1.000**	**1.000**	**1.000**
GPR_{Broad}	**0.433**	0.000	**0.543**	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-week-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	**0.371**	0.000	**1.000**	0.000
GPR_{Act}	**1.000**	**1.000**	**0.731**	**1.000**
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	0.000	0.000
RV	0.000	0.000	0.000	0.000
One-month-head forecast				
GPR	0.000	0.000	0.000	0.000
GPRS	0.000	0.000	0.000	0.000
GPR_{Treat}	0.000	0.000	**1.000**	**0.517**
GPR_{Act}	**1.000**	**1.000**	**0.630**	0.000
GPR_{Broad}	0.000	0.000	0.000	0.000
GPR_{Narrow}	0.000	0.000	**0.863**	0.000
RV	**0.685**	**0.616**	0.000	0.000

Note. We use bold numbers that stand for p values of the model that is greater than 0.25. The p value of 1.000 indicates that a model has the best performance among all the testing models. MSFE refers to the mean squared forecast error, and MAFE refers to the mean absolute forecast error. The lags of the RV are set to 66.

Hamori [64] and Pu et al. [77] set the p value alpha to be 0.1, whereas Liu et al. [50], Mei et al. [62], and Liang et al. [15] set the p value alpha to be 0.25. Since we use the same method as [50] and focus on the volatility prediction as Liang et al. [15], we set the threshold p value to be 0.25.

Table 7 shows the results of short- and long-term predictive ability with the monthly RV and GPR factors. It is shown in the table that the model with GPR_{Act} passes the MCS test under both the MSFE criterion and the MAFE criterion.

It is interesting to see that although GPR_{Act} has no significant impact on the stock volatility, it has the best predictive power among all six types of GPR indices. Because GPR_{Act} represents the realization of geopolitical events, it does contain the real information that determines the change of stock market; thus, it has the best predictive power among other GPR indices.

4.4. Economic Value Analysis. In this section, we employ an out-of-sample trading strategy to analyze the economic value of the benchmark GARCH-MIDAS model and its extensions. Following [62, 77], we pay attention to investors with a mean-variance utility function and allocates their assets between CSI 300 and a risk-free asset. The utility is defined as follows:

$$U_t(\widehat{r}_t) = E_t\left(w_t^*\widehat{r}_t + r_{t,f}\right) - \frac{1}{2}\gamma \mathrm{Var}_t\left(w_t^*\widehat{r}_t + r_{t,f}\right), \tag{13}$$

where w_t^* is the optimal weight of CSI 300 in this portfolio; $\widehat{r}_t$ is the excess return $(\widehat{r}_t = r_t - r_{t,f})$, r_t is the CSI 300 return; $r_{t,f}$ is the risk-free rate, and we use the three-month interbank offered rate to denote the risk-free rate; andγ is a risk aversion coefficient. The portfolio returns (R) is $w_t^*\widehat{r}_t + r_{t,f}$. We calculate the ex ante optimal weight as follows:

$$w_t^* = \frac{1}{\gamma}\left(\frac{\widehat{r_{t+1}}}{\widehat{\sigma_{t+1}^2}}\right). \tag{14}$$

Table 8 indicates that the extended GARCH-MIDAS model with the GPR index has gained larger portfolio returns than the benchmark model. Thus, generally speaking, when predicting the short-term CSI 300 volatility, the GPR indices does offer economic value for trading in the CSI 300 market.

4.5. Robustness Checks. Engle et al. [53] and Liu et al. [50] mentioned that different lags of RV (RV_{t-k}) in equations (4) and (5) affect the accuracy when forecasting the volatility using GARCH-MIDAS models, and they use the monthly, biannual, and quarterly lags of RV in the GARCH-MIDAS models for robustness check. Inspired by their ideas, we also add the bimonthly and quarterly lags of RV in equations (5) and (10) in robustness check, to clarify if the extended GARCH-MIDAS models with GPR factors could robustly have a more accurate forecast. Tables 9 and 10 show the MCS testing results with bimonthly and quarterly RVs, and our results are robust with different lags of RVs.

5. Conclusions

This paper focuses on the relationship between the GPR indices and the volatility in CSI 300 based on the GARCH-MIDAS model. We construct different GARCH-MIDAS models with various GPRs in the long-term variance component and by comparing the predictive performance to identify the most valuable GPR index. The results show that first, both GPR and GPRS have a significant positive impact on the volatility in CSI 300, and the coefficient of GPRS is larger than that of GPR, indicating that market participants are paying more attention to the serious GPR and are more sensitive to it. The coefficient of GPR_{Treat} is significant and larger than that of GPR_{Act}, which indicates that in China's stock market, words are more influential than actions. Second, among 18 countries and districts, the GPR in 10 countries and districts has a significant influence on the CSI 300. The GPR_{Turkey}, GPR_{Korea}, $GPR_{Indonesia}$, $GPR_{Saudi\ Arabia}$, $GPR_{Colombia}$, $GPR_{Malaysia}$, and $GPR_{Philippines}$ significantly reduced the volatility in China's stock markets, whereas the GPR_{Brazil}, GPR_{China}, and $GPR_{Venezuela}$ significantly increased the volatility in China's market. Third, with respect to out-of-sample forecasting performance, the GPR_{Act} has the most information about future volatility in CSI 300 in China. When forecasting short-term volatility in CSI 300, GPRAct also helps improve the economic performance. The empirical results suggest that except for a few emerging economies such as Mexico, Argentina, Russia, India, South Africa, Thailand, Israel, and Ukraine, the global and most of the regional GPR have a significant impact on China's stock market. As for predictive potential, GPR_{Act} has the best predictive power among all six types of GPR indices. Considering that GPR is usually unanticipated, these findings shed light on the role of the GPR factors in explaining and forecasting the volatility of China's market returns.

Our results have important implications. First, for global geopolitical risk, investors and policy-makers should pay attention to the changes of the GPR_{Act} index when predicting the long-term volatility of China's stock market. More importantly, the fact that the GPR in most of the countries has a significant impact on volatility in CSI 300 indicates that with the ongoing financial openness of China, China's stock prices have already played their informative role with respect to geopolitical events, and China has become more connected and dependent with the global economic environment.

Data Availability

The stock price data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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