# Geopolitical risk and stock market volatility in emerging markets: A GARCH – MIDAS approach

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**Abstract[#]**

In this study, we offer the following innovations. First, we provide evidence for the predictive content of Geopolitical risk (GPR) for stock volatility in emerging markets. Second, we examine the out-of-sample predictive ability of geopolitical risks for stock volatilities of emerging markets. Third, we employ a methodology (the GARCH-MIDAS technique) which accommodates mixed data frequencies thereby circumventing information loss or any associated bias. We also account for the role of global economic factors as control variables in the model. Our motivation for this study is premised on the dearth of studies on GPR – stock volatility nexus in emerging markets. Thus, using country-specific daily stock returns and monthly GPR data of Caldara and Iacoviello (2018) from January 1975 to May 2020, we test the hypothesis that increase in the geopolitical risk events such as war, terrorism, among others, increase the tendency for stock market volatility. Our findings reveal the following prominent results: (i) emerging stock market volatility responds more positively to geopolitical risks regardless of the GPR proxy; (ii) the decomposed components of GPR (acts and threats) offer better out-of-sample predictability than the composite GPR indices; (iii) act-related GPR is a better predictor of stock market volatility in emerging market than threat-related GPR and (iv) accounting for global economic factors in the predictability analysis is crucial for robust outcomes. We conclude that regardless of the GPR measure, increased incidence of GPR has the tendency to instill volatility in stock market. We offer some implications of our findings for investment and policy decisions.

**Keywords:** Geopolitical risk; Stock market volatility; Emerging markets; GARCH-MIDAS
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## 1. Introduction

This study examines the nexus between geopolitical risk (GPR afterwards) - such as threats of war and terrorism - and stock market volatility in emerging markets using a GARCH-MIDAS approach. This consideration is underscored by the rising level of geopolitical risks in some emerging countries, amidst increase in demand for stocks of emerging countries for hedging and international portfolio diversification purposes (Oloko et al., 2021). Based on the geopolitical risk data by Caldara and Iacoviello (2018), the average level of geopolitical risk of China increased from 0.26 index points[7] (ipts) in the 1990s to 0.55ipts in 2010s. The average level of geopolitical risk of South Korea increased from 0.17ipts to 0.33ipts, while that of Turkey increased from 0.15ipts to 0.34ipts in the same period. Meanwhile, the high level of integration among these markets (emerging markets) has been one of the reasons for their vulnerability to global geopolitical risk (Wilkinson, 2014; Cheng and Chiu, 2018)[8]. It is imperative to note that factors influencing stock market dynamics are not only limited to economic and financial factors, but also include uncertainty-induced shocks (Antonakakis et al., 2017), and prominent among these shocks is geopolitical risk which covers geopolitical tensions, risk of war, military threats and terror attacks (Alqahtani et al., 2020). Moreover, geopolitical risk is distinct from other existing measures of risk and is considered a key determinant of investment decisions and stock market dynamics (Caldara and Iacoviello, 2018; Baur and Smales, 2020). Consequently, events related to insecurity, terrorism, among other political tensions exacerbate the uncertainty in the financial markets which then make investors to postpone or divest their stock investments (Antonakakis et al., 2017).

Furthermore, it has been discovered that regional wars and political crises cause severe variations in stock volatility (Schneider & Troeger, 2006; Nikkinen, Omran, Sahlström & Äijö 2008; Jeribi, Fakhfekh & Jarboui, 2015), hence, when these happen, investors are more concerned about large stock price fluctuations than they do with mild ones (see Homan, 2006; Wang, Ma, Liu and Yang, 2020). In addition to the submission of Choudhry (2010) that events during World War II mark structural breaks in the stock return volatility, the ongoing Russia-Ukraine crisis is

[7] Caldara and Iacoviello (2018) calculate the country-specific index by counting the monthly share of all newspaper articles from 1900 to 2020 (or 1985 to 2020 for the Recent Index) that both (1) meet the criterion for inclusion in the GPR index and (2) mention the name of the country or its major cities. Each index is expressed as a monthly share of newspaper articles.

[8] Emerging markets are faced with geopolitical tension mostly spilled over to them from developed economies: US-China trade wars, Iran sanctions, the role of Russia and the future of shale, oil markets turbulent, and all that shows no sign of ending (see Mei et al., 2020; Dogan et al. 2021).

also a perfect example, as the conflict added considerably to the already ailing stock market[9]. The foregoing summing up the fact that stock market can be sensitive to GPR shocks.

Consequently, a precise forecast of stock return volatility is usually of utmost priority to investors in periods characterized by uncertainty-induced shocks such as geopolitical risk, which are systematic and therefore not fully diversifiable (Pástor and Veronesi, 2013). Establishing this, Caldara and Iacoviello (2018) posit that geopolitical risk offers some potential predictive contents for stock returns and has the ability to alter the economic cycles' dynamics and investment decisions. Given the foregoing, studies have established the sensitivity of stock market to geopolitical risk (see Brounen and Derwall, 2010; Aslam and Kang, 2015; Antonakakis et al., 2017; Balcilar et al., 2018; Plakandaras et al., 2019; Alqahtani et al., 2020; Baur and Smales, 2020; Zhou et al., 2020; Smales, 2021; Yang et al., 2021).

Within the precinct of this growing body of empirical studies, our study explores the predictability of GPR for stock return volatility given the dearth of empirical literature in this area[10]. Subsequently, relying on the risk – return hypothesis where investors require a 'bribe' in the form of higher potential returns to take on extra risk (Müller et al., 2011), we extend our analysis to cover out-of-sample predictability of GPR for stock market volatility as reliance on in-sample predictability solely may lead to a biased outcome (see Rapach and Zhou, 2013). Thus, rather than focusing on stock returns, our analysis is rendered for stock market volatility relying on the intuition that investors are wary to invest in turbulent times and therefore information about the market risks (where the market volatility serves as a good proxy) accentuated by geopolitical risk is crucial for investment decisions. We therefore test the hypothesis that increase in the geopolitical risk events such as war, terrorism, among others, increase the tendency for stock market volatility. To the best of our knowledge, this is the first paper to evaluate the out-of-sample predictive value of geopolitical risk in stock return volatility.

Furthermore, we employ a GARCH-MIDAS[11] approach that allows for the use of series in their available 'natural' form rather than restricting our analysis to a uniform frequency when in

[9]https://www.nytimes.com/2022/02/23/business/stock-market-correction.html; https://journalnow.com/business/investment/personal-finance/the-russia-ukraine-conflict-is-rattling-the-stock-market-here-s-what-investors-should-do/article_fea029e5-e139-503e-8cd3-5812de66201c.html

[10] We acknowledge recent studies on GPR and energy market volatility (see for example Liu, Han and Xu, 2021; Wang et al., 2021), with the conclusion that GPR has the predictability power for energy market volatility. The foregoing also holds for GPR and Bitcoin (see Aysan et al., 2019).

[11] GARCH-MIDAS is the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (MIDAS).

fact the variables of interest (the predicted and the predictor series) are available at different frequencies. Actually, the GARCH-MIDAS model is appropriate if the dependent variable is of high frequency and the independent variable is of low frequency. This is the case in our study. The dependent variable, stock return volatility, is of high frequency (daily) while the independent variable of interest, geopolitical risk, is of monthly (relatively lower) frequency for the selected emerging economies (see Ghysels, Santa-Clara, and Valkanov, 2006; Engle, Ghysels and Sohn, 2013). Thus, the objective of this study is to forecast daily stock return volatility[12] with monthly geopolitical risks and since the former is a higher frequency than the latter, the GARCH-MIDAS model[13], comes in handy. Since both the dependent and the independent variables are used in their "natural" frequencies, the loss of information associated with averaging the daily volatility to a lower GPR monthly frequency (Clements and Galvão, 2008; Das et al., 2019) is circumvented.

Sequel to our attraction to GARCH-MIDAS, studies such as Wang (2010), Girardin and Joyeux (2013), Fang, Chen, Honghai and Qian (2018), Wang et al. (2020), Ndako, Salisu and Ogunsiji (2021) among others, have adopted the same method for the same reason espoused in this paper. Consequently, a GARCH approach is used by Wang (2010) to show that the volatility of inflation causes stock market volatility in China. Similarly, Girardin and Joyeux (2013) apply the Mixed Data Sampling (MIDAS) methodology to explain the Chinese A and B-share markets' long-run volatility estimated from daily squared returns using monthly data on macroeconomic variables. Similarly, Fang et al. (2018) adopt GARCH-MIDAS model to examine the predictability of global economic policy uncertainty (GEPU) for gold market behaviour, and their results suggest a strong forecasting power of GEPU for future monthly volatilities for the aggregate global gold futures market (out-of-sample tests inclusive). In particular, probing the predictive content of GPR for Islamic stock return volatility with special interest in Indonesia and Malaysia, Ndako et al. (2021) conclude that GPR heighten the return volatility in these countries. In other words, Islamic stock return volatility is vulnerable to GPR in the two countries.

To further validate our results, we use different variant of GPRs (both global and country-specific) such as threats and act, to assess the predictive prowess of GPR for stock return volatility.

[12] This stems out of the fact that daily information is of paramount importance to investors while making investment decisions, as waiting for a longer time usually has some associated costs. This is often referred to as waiting cost (see Eschenbach et al., 2009).

[13] An alternative variant is the Autoregressive Distributed Lag (ADL)-MIDAS model which incorporates a higher frequency predictor with a low frequency predicted series. This is relevant here since the reverse is the case in terms of the distribution of the data frequencies.

In addition to examining the effect of global GPR (on aggregate), we consider its decomposition into act-related and threat-related, referred to as GPR acts (GPRA) and GPR threat (GPRT), respectively. The significance of considering the decomposed components of global GPR is well documented in Mei et al. (2020), where GPRA is found to contribute more to the long-term oil volatility forecasts than GPRT.

Foreshadowing our results, we find that stock market volatility responds more positively to geopolitical risks. Further analysis involving forecast evaluation shows that both the global and country-specific GPRs have significant predictive contents for out-of-sample stock market volatility in emerging markets regardless of the forecast horizons as the proposed GARCH-MIDAS-X model with GPR outperforms the benchmark model (GARCH-MIDAS-RV with realized volatility). Nonetheless, the decomposed components of GPR (acts and threats) offer better out-of-sample predictability than the composite GPR indices while the act-related GPR is a better predictor of stock market volatility in emerging market than threat-related GPR. Finally, we find that accounting for global economic factors in the predictability analysis is crucial for robust outcomes.The remainder of the paper is organized as follows: Section 2 provides a brief review of the literature; Section 3 outlines the methodology; Section 4 highlights some data issues and provides relevant descriptive statistics; Section 5 discusses the research findings with relevant implications for investment and policy decision making while Section 6 concludes the paper.

## 2. Review of relevant literature

Caldara & Iacoviello (2018) define geopolitical risk as the risk associated with terrorist acts, wars, and tensions between states that affect the normal and peaceful course of international relations. As stock market volatility has been established to increase in reaction to bad news (see Salisu and Oloko, 2015; Wang et al., 2020), higher geopolitical risks may be expected to induce higher stock market volatility. Theoretical analysis of investment in a risky environment can be explained by Keynesian hypothesis of “liquidity trap”. This explains that demand for investment in a turbulent economy (facing high geopolitical risk, for example) is generally low, leading to over-accumulation of liquidity as investment risk (volatility) increased and investment confidence reduced. This suggests existence of positive relationship between geopolitical risk and stock market volatility. As geopolitical risk comprises domestic and global political and socio-economic shocks which unavoidably affect the stock market, it is regarded as a systematic risk; risk that cannot be diversified. More importantly, as geopolitical risk increases investors' panic and reduces investors' confidence to stimulate panic and unusual investment dealings, it is expected to induce higher stock market volatility. Similarly, GPR can impact the stock market through the cash holding channel, as investors usually delay their investment decisions as a result of panic associated with war, conflict among other components of GPR. This is anchored on the Pecking Order Theory of Myers and Majluf 1984 (see also Salisu, Lasisi and Tchankam 2021). Moreover, GPR usually causes the movement of capital from countries facing high geopolitical risk to countries experiencing a relatively low GPR (see also Caldara and Iacoviello, 2018). In addition, the Arbitrage Pricing Theory – APT – equally captures the relationship between GPR and stock returns quite perfectly as it uses a number of factors rather than a single market index to illustrate the link between the two. As opined by Kisman and Restiyanita (2015) there are a few alternative theories (such as Capital Asset Pricing Model – CAMP) that can be used to model the relationship between risk and stock return, the APT is the most accurate. The foregoing theories suggest what the periods characterised by high GPR would mean for stock market volatility.

Recent studies have examined the effect of geopolitical risk on stock returns (Hoque and Zaidi, 2020; Salisu et al., 2021; Smales, 2021) and their findings suggest a negative relationship between them. Our study differs from the existing literature as it essentially focuses on stock market volatility rather than the return series and also within the GARCH-MIDAS framework. Since both existing and potential investors often consider the risk associated with financial market (technically measured with volatility) when making investment decisions, focusing on stock market volatility rather than returns (unlike Hoque and Zaidi, 2020) would have more insightful implications for investment as well as policy decision making. Unlike the Smales (2021) which employs the (multivariate) GARCH model and Salisu et al. (2021) which employ a variant of autoregressive distributed lag model, both of which rely on uniform frequency, we differ by using the GARCH-MIDAS model on two grounds. One, it is useful for the analysis of the response of stock market volatility to an exogenous factor like geopolitical risk. Two, given the availability of data for the two variables of interest where stock market volatility is of daily frequency and geopolitical risk is of monthly frequency, the use of GARCH-MIDAS is required to accommodate the variables in their "natural" frequencies which by extension helps to circumvent information loss and improves predictability. Undoubtedly, the conventional GARCH models can equally serve this purpose, however, the second attraction to the GARCH-MIDAS gives it an edge over the former. Overall, recent studies have documented that the GARCH-MIDAS class specifications proposed by Engle et al. (2013) demonstrate superior forecasting abilities for the stock market volatility (see for example, Fang et al. 2020; Wang et al., 2020)[14] albeit for different exogenous factors. Thus, our study extends the literature to accommodate the role of GPR in the predictability of stock market volatility.

## 3. Methodology

The GARCH-MIDAS framework is employed to examine the predictive role of the global geopolitical risk (GPR) in stock market volatility. As noted previously, the adopted methodology permits the use of mixed data frequencies and therefore circumventing the need to limit the variables of interest to the same (low) frequency. Ordinarily, in a situation where one variable is available at a high frequency (stock returns in our case) and the other variable at a low frequency (GPR in our case), the analysis is restricted to the latter frequency which may lead to information loss and biased outcomes. Thus, we accommodate the high and low frequencies observed for the two series in order to ensure that greater variability and more robust information are captured in the estimation process with greater potential for improved forecast outcomes (as further demonstrated in the results section which further offers some reasonable basis for considering mixed frequencies for predictability analysis).[15]

Given a daily stock return series computed as log return - $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ represents the price for day *i* in month *t* with $t = 1, \ldots, T$ and $i = 1, \ldots, N_t$ denoting the monthly and daily frequencies, respectively, and $N_t$ is the number of days in a given month *t*, we construct a GARCH-MIDAS-X model where the geopolitical risk (in natural logs) serves as a predictor. Essentially, there are two components involving the mean and conditional variance equations, while the latter is further divided into short and long run components to accommodate the predictor series.

[14] Similar evidence was found by studies applying GARCH-MIDAS on the relationship between geopolitical risk and oil returns volatility (see for example, Mei et al., 2020; Wang et al., 2021) on the predictability of cryptocurrencies (see Conrad et al., 2018) and on the predictability of stock returns without accounting for the role of geopolitical risk (Asgharian et al., 2013).

[15] The technical details and computational advantages of using the MIDAS regressions are well documented in Engle et al. (2013).

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \quad \varepsilon_{i,t} \big| \Phi_{i-1,t} \sim N(0,1), \quad \forall \ i = 1, \dots, N_t \tag{1}$$

$$h_{i,t} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_i} + \beta h_{i-1,t} \tag{2}$$

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k(w_1, w_2) X_{i-k}^{(rw)} \tag{3}$$

where equation (1) defines the mean equation while equations (2) and (3) are for the conditional variance components specified respectively for short and long run components. In terms of the definition of parameters, $\mu$ is the unconditional mean of the return series as specified in equation (1); $h_{i,t}$ is the short-run component of a high frequency, and as specified in equation (2), it follows the $\mathrm{GARCH}(1,1)$ process, where $\alpha$ and $\beta$ are the ARCH and GARCH terms, respectively, conditioned to be positive and/or at least zero ($\alpha > 0$ and $\beta \geq 0$) and sum up to less than unity $(\alpha + \beta < 1)$; $\tau_t$ captures the long-run component that incorporates the exogenous macroeconomic series (or realized volatility where there is no macroeconomic series), and it involves repeating the monthly value throughout the days in that month. The superscript "$(rw)$" in equation (3) denotes the implementation of a rolling window framework (which allows the secular long-run component to vary daily), while $m$ represents the long-run component intercept. The focus of our analysis is the MIDAS slope coefficient ($\theta$) that indicates the predictability of the incorporated exogenous predictor $X_{i-k}$ where $\phi_k(w_1, w_2) \geq 0, \ k = 1, \dots, K$ is the weighting scheme that must sum to one for the parameters of the model to be identified; and $K$ is chosen based on the log-likelihood statistic for each pair of the predicted and the predictor series in order to filter the secular component of the MIDAS weights.

For the out-of-sample forecast performance evaluation, we compare the forecasts of our proposed GARCH-MIDAS predictive model (involving GPR), i.e. GARCH-MIDAS-X with that of the conventional GARCH-MIDAS specifications that include realized volatility (GARCH-MIDAS-RV). The out-of-sample forecast performance is evaluated in a rolling window setting for four forecast horizons that correspond to short- and long-run predictability ($h$ = 10, 30, 60, 180). Given that the contending models are not nested, we employ the modified version of the Diebold and Mariano (1995) (DM) test as per Harvey, Leybourne, and Newbold (1997) test which calculates the p-value and addresses the issue with the assumption of zero covariance at 'unobserved' lags to formally ascertain whether the forecast errors associated with the contending models differ significantly. The test statistic is usually formulated as:

$$DM\ Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{4}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean of the loss differential $d_t \equiv l(\varepsilon_{xt}) - l(\varepsilon_{rvt})$; $l(\varepsilon_{xt})$ and $l(\varepsilon_{rvt})$ are the loss functions of the forecast errors ($\varepsilon_{xt}$ and $\varepsilon_{rvt}$, respectively) that are associated with the GARCH-MIDAS-X and GARCH-MIDAS-RV, respectively; and $V(d_t)$ is the unconditional variance of the loss differential $d_t$. The modified DM test statistic as per Harvey, Leybourne, and Newbold (1997) is given as:

$$DM^* = \left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}}\right) DM \tag{5}$$

where $DM^*$ denotes the modified DM statistic and $h$ is the forecast horizon. We test the null hypothesis that the accuracy of the two series of forecasts is the same, that is, $H_0 : E(d_t) = 0$, against the alternative $(H_1 : E(d_t) \neq 0)$ that the proposed model (that is, the GARCH-MIDAS-X model) is more accurate than the benchmark model (that is, the GARCH-MIDAS-RV model). Based on the modified DM test by Harvey, Leybourne, and Newbold (1997), a statistically significant negative statistic implies the adoption of the GARCH-MIDAS-X model while the benchmark (GARCH-MIDAS-RV) model is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical.

## 4. **Data and Preliminary Analysis**

Our datasets consist of stock prices of 11 major emerging economies in the world and their respective geopolitical risk (GPR) index values obtained from the website of Matteo Iacoviello[16]. Our choice of countries is essentially based on data availability, especially GPR data which is only available for 19 emerging economies. Of these 19, we could access stock prices[17] for only 11 countries. This study employs historical data. However, combining dependent and independent variables determines the scope for each country. The oil market uncertainty index and global economic policy uncertainty are used as control variables in this study to capture potential effect of global economic uncertainty on the domestic stock market volatility. With increasing financial market globalization of emerging countries, higher global economic uncertainty may be expected to increase stock market volatility in these countries (see Alqahtani et al., 2020; Lin and Su, 2020; Yang et al., 2021). Generally, the start date for the data used in this study is January 1997 (constrained by the availability of global economic policy uncertainty data) and the end date is May 2020 (constrained by the availability of oil market uncertainty index data[18]). Meanwhile, historical data for stock price index of some countries starts after 1997, making those countries to have shorter samples.

The eventual data scope is presented in Table 1. The table shows that Argentina, China, India, Korea, and South Africa have the same number of observation covering 281 months. The difference in their daily observations was due to national holidays, as the daily data for all countries are on 5-day a-week basis. Obviously, the data scope of the mentioned five countries and two others (Brazil and Hong Kong) covers a series of international political and economic events including the global financial crisis (GFC), while the study scope for the remaining three countries, that is, Colombia, Philippines, and Turkey only covers post GFC global political and economic events. Therefore, it may not be out-of-place to suspect some level of heterogeneity in terms of the response of the individual stock market volatilities to geopolitical risks.

[16]Please use this link to download the GPR data, https://www.matteoiacoviello.com/gpr.htm. Technically-minded readers are referred to Caldara and Iacoviello (2018) for computational details of the GPR indices.
[17] Available on www.investing.com
[18] See Nguyen et al. (2021): https://sites.google.com/site/nguyenhoaibao/oil-market-uncertainty?authuser=0

**Table 1: Data scope**

| Countries | Stock Index | Data coverage | Daily obs. | Monthly obs. |
|---|---|---|---|---|
| **Argentina** | MERV | Jan., 1997 – May, 2020 | 5762 | 281 |
| **Brazil** | BVSP | Jan., 2001 - May, 2020 | 4804 | 233 |
| **China** | SSEC | Jan., 1997 - May, 2020 | 5673 | 281 |
| **Colombia** | FTWICOLL | July, 2012 - May, 2020 | 2056 | 95 |
| **Hong Kong** | HSI | Dec., 2000 - May, 2020 | 4827 | 234 |
| **India** | NSEI | Jan., 1997 - May, 2020 | 5822 | 281 |
| **Korea** | KS11 | Jan., 1997 - May, 2020 | 5871 | 281 |
| **Malaysia** | KLSE | May, 2010 - May, 2020 | 2476 | 121 |
| **Philippines** | PSE | Mar., 2012 - May, 2020 | 1966 | 99 |
| **South Africa** | JTOPI | Jan, 1997 - May, 2020 | 5869 | 281 |
| **Turkey** | XSIST | Jan., 2009 - May, 2020 | 2865 | 137 |

Note: obs. implies number of observations. Daily observations represent the number of observations for stock returns, while monthly observations present the number of observations for the exogenous/control variables. These consist of the main explanatory variable, GPR (Aggregate, Act, and Threat), and the control variables, oil market uncertainty index and global economic policy uncertainty.

Table 2 illustrates the preliminary statistics for the study. This consists of the descriptive statistics, autocorrelation test and conditional heteroscedasticity test for stock returns (used to estimate the model-based stock market volatility within the GARCH-MIDAS framework) and the exogenous/control variables. The table is partitioned into three panels. Panel A presents the preliminary statistics for stock returns, in daily frequency; Panel B is for the country-specific geopolitical risk, which is the first main explanatory variable and available in monthly frequency while Panel C is for the global GPR with its decomposed series, GRP Act (GPRA) and GPR threat (GPRT). The preliminary statistics for the control variables, that is, the oil market uncertainty index and the global economic policy uncertainty index, are also presented in Panel C.

The table shows that Argentina has the highest average stock returns (0.07%) and the lowest geopolitical risk (0.03 index point). More so, China and Korea with relatively high average geopolitical risk (0.46 and 0.29 index points, respectively) have relatively low stock returns (0.02). This suggests inverse relationship between geopolitical risk and stock market performance. Meanwhile, Columbia and Philippines have negative average stock returns despite their relatively low geopolitical risk. This suggests that low geopolitical risk may not necessarily cause better stock market performance. More so, the table shows that the average global GPR is 99.15 index point, while the average values for GRPA and GPRT are 103.99 and 95.87, respectively. This suggests that changes in global GPR are more influenced by the act-related geopolitical risk than the threat-related geopolitical risk. Furthermore, stock returns for all the emerging economies (with the exception of Philippines and Turkey) are negatively skewed and leptokurtic, with kurtosis value in excess of three. The GPR values are averagely high for all the countries with most of the values clustering around the mean. Turkey records the highest GPR value for the group followed by Korea, China and Hong Kong. Understandably so, Turkey faces a constant threat from ISIS (Islamic State in Syria and Levante) while hostilities remain between Korea republic (or South Korea) and peoples republic of Korea (North Korea). Similar situation exists between China and its neighbours, in particular Hong Kong.

**Table 2: Preliminary Statistics**

| Variables | Mean | Std. Dev | Skew. | Kurt. | $Q^2(5)$ | $Q^2(10)$ | ARCH(5) | ARCH(10) |
|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: Stock returns** | | | | |
| Argentina | 0.07 | 2.34 | -1.80 | 37.22 | 109.01*** | 131.81*** | 19.46*** | 10.65*** |
| Brazil | 0.04 | 1.81 | -0.39 | 10.10 | 2765.4*** | 3956.5*** | 342.57*** | 180.60*** |
| China | 0.02 | 1.59 | -0.42 | 8.03 | 691.25*** | 1066.6*** | 91.61*** | 53.98*** |
| Colombia | -0.06 | 1.71 | -1.84 | 38.97 | 937.50*** | 1336.3*** | 176.71*** | 100.64*** |
| Hong Kong | 0.01 | 1.43 | -0.07 | 11.53 | 2234.4*** | 3359.4*** | 268.93*** | 159.02*** |
| India | 0.04 | 1.52 | -0.35 | 11.94 | 871.88*** | 1427.2*** | 115.89*** | 72.74*** |
| Korea | 0.02 | 1.68 | -0.31 | 8.22 | 1678.5*** | 2738.9*** | 207.23*** | 114.86*** |
| Malaysia | 0.005 | 0.63 | -0.42 | 14.01 | 1145.7*** | 1423.2*** | 183.40*** | 97.31*** |
| Philippines | -0.03 | 1.41 | 0.74 | 17.48 | 194.19*** | 283.62*** | 32.25*** | 21.88*** |
| South Africa | 0.04 | 1.36 | -0.42 | 9.82 | 1757.6*** | 2663.2*** | 208.70*** | 117.35*** |
| Turkey | 0.05 | 12.22 | 0.17 | 1399.1 | 356.37*** | 356.38*** | 69.70*** | 34.75*** |
| | | | | **Panel B: Country-specific geopolitical risks** | | | | |
| Argentina | 0.03 | 0.03 | 3.71 | 25.18 | 10.12* | 18.24* | 1.97* | 1.44 |
| Brazil | 0.05 | 0.03 | 2.26 | 10.29 | 5.64 | 7.89 | 1.01 | 0.65 |
| China | 0.46 | 0.24 | 1.52 | 5.52 | 18.82*** | 39.19*** | 3.04** | 2.46*** |
| Colombia | 0.04 | 0.04 | 3.00 | 17.31 | 21.12*** | 21.39** | 4.47*** | 2.19** |
| Hong Kong | 0.04 | 0.05 | 4.30 | 26.43 | 9.00 | 58.25*** | 2.81** | 12.12** |
| India | 0.21 | 0.14 | 3.29 | 17.03 | 3.48 | 6.75 | 0.63 | 0.56 |
| Korea | 0.29 | 0.25 | 2.59 | 11.76 | 41.86*** | 47.05*** | 6.14*** | 3.33*** |
| Malaysia | 0.04 | 0.07 | 10.23 | 138.85 | 0.05 | 0.09 | 0.01 | 0.01 |
| Philippines | 0.04 | 0.04 | 2.34 | 9.22 | 20.3*** | 20.85*** | 3.24*** | 1.72* |
| South Africa | 0.06 | 0.03 | 1.97 | 9.33 | 3.34 | 3.56 | 0.66 | 0.34 |
| Turkey | 0.23 | 0.18 | 2.02 | 9.10 | 13.24** | 14.31 | 2.60** | 1.50 |
| | | | | **Panel C: Explanatory and Control variables** | | | | |
| GPR | 99.15 | 51.27 | 4.55 | 32.72 | 2.16 | 2.22 | 0.39 | 0.19 |
| GPRA | 103.99 | 85.46 | 5.56 | 44.51 | 1.46 | 1.51 | 0.27 | 0.13 |
| GPRT | 95.87 | 38.31 | 2.77 | 15.61 | 15.06** | 15.58 | 2.65** | 1.34 |
| GEPU | 122.48 | 62.24 | 1.71 | 6.68 | 55.32** | 97.58** | 9.72*** | 8.46** |
| OMUI | 0.79 | 0.19 | 1.87 | 11.01 | 123.66*** | 123.78*** | 33.59*** | 16.23*** |

Note: Std. Dev. is the standard deviation, Skew is skewness, Kurt is kurtosis, while *** and ** & * imply the rejection of the null hypothesis at 1% 5% & 10% levels of significance, respectively. Stock returns is computed as 100*log (stock price/stock price (-1)). Also, the $Q^2(k)$ statistics are obtained from the Ljung-Box test for serial correlation respectively using the squared residuals of the test regressions where k=5, 10, 20. The ARCH (k) reports the F-statistics of the ARCH-LM test used to test for conditional heterocsedasticity. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F-distributed) test is that there is no conditional heteroscedasticity. GPR represents aggregate geopolitical risk, while GPRA is geopolitical risk act, GPRT is geopolitical risk threat, GEPU is global economic policy uncertainty and OMUI is oil market uncertainty index.

Our preliminary analyses include results for the test for conditional heteroscedasticity and higher order autocorrelation at lags 5 and 10. The formal tests employed are the Autoregressive Conditional Heteroscedasticity (ARCH) test and Q2-statistics, respectively (see the results in Table 2). As may be observed, stock returns for all the countries considered exhibit ARCH effect and higher order correlation at all the specified lags. This can be attributed to the high frequency nature of the data. Meanwhile for the GPR index, although ARCH effect and higher order correlation is not present in all the lags, it is found in at least one lag for 60 percent of the countries.

Therefore, given the presence of ARCH effect, serial correlation and the mixed frequency of the data used, the GARCH-MIDAS model framework will be the most suitable approach for the analysis.

To examine the effect of country-specific and global geopolitical risk on market volatility, we specify and compare the in-sample and out-of-sample forecast performance of four GPR-based models with the baseline GARCH-MIDAS model (GARCH-MIDAS with realized volatility). The four GPR-based GARCH-MIDAS (GARCH-MIDAS-X) can be described as follows: The first model expresses stock return volatility as a function of country-specific geopolitical risk (GPR); the second expresses stock return volatility as a function of global (aggregate) geopolitical risk (GGPR); the third and fourth are for stock return volatility against global act-related geopolitical risk (GGPRA) and global threat-related geopolitical risk (GGPRT), respectively. Thus, we have four variants of GARCH-MIDAS-X model (GARCH-MIDAS-GPR, GARCH-MIDAS-GGPR, GARCH-MIDAS-GGPRA, and GARCH-MIDAS-GGPRT) to be compared with the baseline GARCH-MIDAS model.

To examine the significance of financial globalization, we augment the GARCH-MIDAS-X models to include relevant control variables (oil market uncertainty and global economic policy uncertainty) such that we have four variants of GARCH-MIDAS-X with control variables, accordingly. To avoid proliferation of parameters, we use the principal component approach to develop an index that accommodates the best fit of the combined predictors (involving both the GPR and the control variables). Thereafter, the index is used as an exogenous predictor rather than the GPR in the GARCH-MIDAS model. We employ the correlation matrix when computing the decomposition of the principal components as the alternative method involving the covariance matrix requires that the variances of the underlying variables of interest must be similar, which is not the case for our variables.

**Table 3: Principal Components Analysis (Eigenvalues): (Sum = 3, Average = 1)**

| | Eigenvalue | Eigenvalue Proportion | Eigenvalue Cumulative Proportion | | Eigenvalue | Eigenvalue Proportion | Eigenvalue Cumulative Proportion |
|---|---|---|---|---|---|---|---|
| **Argentina** | | | | Malaysia | | | |
| **1** | 1.456443 | 0.4855 | 0.4855 | 1 | 1.387406 | 0.4625 | 0.4625 |
| **2** | 0.938174 | 0.3127 | 0.7982 | 2 | 0.991721 | 0.3306 | 0.7930 |
| **3** | 0.605383 | 0.2018 | 1.0000 | 3 | 0.620874 | 0.2070 | 1.0000 |
| **Brazil** | | | | Philippine | | | |
| **1** | 1.474871 | 0.4916 | 0.4916 | 1 | 1.388141 | 0.4627 | 0.4627 |
| **2** | 0.931820 | 0.3106 | 0.8022 | 2 | 0.990091 | 0.3300 | 0.7927 |
| **3** | 0.593309 | 0.1978 | 1.0000 | 3 | 0.621768 | 0.2073 | 1.0000 |
| **China** | | | | South Africa | | | |
| **1** | 1.713877 | 0.5713 | 0.5713 | 1 | 1.461779 | 0.4873 | 0.4873 |
| **2** | 0.866765 | 0.2889 | 0.8602 | 2 | 0.940568 | 0.3135 | 0.8008 |
| **3** | 0.419358 | 0.1398 | 1.0000 | 3 | 0.597652 | 0.1992 | 1.0000 |
| **Columbia** | | | | Turkey | | | |
| **1** | 1.436732 | 0.4789 | 0.4789 | 1 | 1.601368 | 0.5338 | 0.5338 |
| **2** | 1.002026 | 0.3340 | 0.8129 | 2 | 0.986466 | 0.3288 | 0.8626 |
| **3** | 0.561242 | 0.1871 | 1.0000 | 3 | 0.412166 | 0.1374 | 1.0000 |
| **Hong Kong** | | | | Global GPR | | | |
| **1** | 1.825607 | 0.6085 | 0.6085 | 1 | 1.386749 | 0.4622 | 0.4622 |
| **2** | 0.685418 | 0.2285 | 0.8370 | 2 | 0.991524 | 0.3305 | 0.7928 |
| **3** | 0.488975 | 0.1630 | 1.0000 | 3 | 0.621727 | 0.2072 | 1.0000 |
| **India** | | | | Global GPR Act | | | |
| **1** | 1.383207 | 0.4611 | 0.4611 | 1 | 1.380165 | 0.4601 | 0.4601 |
| **2** | 1.041345 | 0.3471 | 0.8082 | 2 | 1.000780 | 0.3336 | 0.7936 |
| **3** | 0.575448 | 0.1918 | 1.0000 | 3 | 0.619054 | 0.2064 | 1.0000 |
| **Korea** | | | | Global GPR Threat | | | |
| **1** | 1.413914 | 0.4713 | 0.4713 | 1 | 1.464008 | 0.4880 | 0.4880 |
| **2** | 1.022393 | 0.3408 | 0.8121 | 2 | 0.930359 | 0.3101 | 0.7981 |
| **3** | 0.563694 | 0.1879 | 1.0000 | 3 | 0.605633 | 0.2019 | 1.0000 |

Note: The Eigenvalues must sum to three (3) since 3 factors (and by implication, 3 principal components) are involved. The proportion for each principal component is determined by taking the ratio of the corresponding Eigenvalue and the sum of all the Eigenvalues for the three principal components.

The results are summarized in Table 3 and the factor loadings[19] are normalized so the observation scores have norms proportional to the eigenvalues. As shown in Table 3, we find that the first two principal components (1 & 2 in the table) explain roughly 80% of the information contained in the correlation matrix for all the units considered. In other words, given that dimensionality reduction is desired, our analysis indicates that we can reduce the underlying dimensionality of the problem from 3 to 2, while retaining nearly 80% of the original information.

[19] The results for the Eigenvectors (loadings) are suppressed for want of space but are available upon request from the authors.

Thus, we use in our further analysis the average of the first two principal components as these components capture the majority of variations in the considered factors.

## 5. Main findings

In this section, we present the results of predictability of country-specific and global GPR for stock volatility and the forecast performance of GARCH-MIDAS-X models with and without control variables vis-à-vis the benchmark model which is the conventional GARCH-MIDAS model with realized volatility (GARCH-MIDAS-RV). For the purpose of emphasis, our study contributes to the literature in three ways. First, it provides evidence for the predictive content of country-specific and global GPR for stock return volatilities in emerging markets. Second, it examines the out-of-sample predictive power of geopolitical risks in stock volatilities of emerging markets. Third, it employs a methodology that accommodates mixed data frequency thereby circumventing information loss or any associated bias. Our parameter estimates are as follows; the unconditional mean stock returns $(\mu)$, the ARCH term $(\alpha)$, the GARCH term $(\beta)$, the slope coefficient $(\theta)$, the adjusted beta polynomial weight $(\omega)$ and the long run constant term (m). We consider 10-day out-of-sample forecast (h=10) as the short run forecast, 30- to 60-day ahead forecast as the medium term forecast and 180-day ahead (h=180) forecast as the long term out-of-sample forecast.

### 5.1 Stock market volatility and country-specific geopolitical risk

Table 4 presents the predictability results for 11 emerging economies. This is the result of the GARCH-MIDAS-X model with country-specific geopolitical risk. The results show that across the emerging economies, the sum of ARCH and GARCH coefficients is less than one, implying that the impact of any shock on the emerging stock markets tends to be transient although may persist over a long period given that the sum is close to one. In essence, we find evidence for high but mean reverting volatility persistence. All the estimates of adjusted beta weight for all the countries are greater than one and statistically significant; with the exception of Brazil, Colombia, Hong Kong, Malaysia, and South Africa where although estimates are greater than one, they are not significant. The result for $(\omega)$ shows that the weighting scheme assigns higher weight to immediate past observations than those distinctly far apart.

**Table 4: Predictive Power of Geopolitical Risk for Stock Returns (Country-Specific)**

| | | $\mu$ | $\alpha$ | $\beta$ | $\theta$ | $w$ | $m$ |
|---|---|---|---|---|---|---|---|
| **Argentina** | Without control | $0.0011^{***}$ | $0.1651^{***}$ | $0.7882^{***}$ | $0.0160^{***}$ | $2.4788^{***}$ | $0.0001^{***}$ |
| | | [0.0002] | [0.0050] | [0.0072] | [0.0022] | [0.7124] | [0.0000] |
| | With control | $0.0012^{***}$ | $0.1790^{***}$ | $0.7711^{***}$ | $0.0473^{***}$ | $7.4766^{***}$ | $0.0006^{***}$ |
| | | [0.0002] | [0.0056] | [0.0077] | [0.0060] | [2.812] | [0.0000] |
| **Brazil** | Without control | 0.0008 | $0.0807^{***}$ | $0.8897^{***}$ | $-0.0012^{**}$ | 4.4611 | $0.0003^{***}$ |
| | | [0.0002] | [0.0062] | [0.0091] | [0.0006] | [4.5914] | [0.0000] |
| | With control | 0.0008 | $0.0805^{***}$ | $0.8890^{***}$ | $-0.0057^{***}$ | 3.7864 | $0.0002^{***}$ |
| | | [0.0002] | [0.0062] | [0.0093] | [0.0021] | [4.4037] | [0.0000] |
| **China** | Without control | 0.0002 | $0.0804^{***}$ | $0.9116^{***}$ | $-0.0002^{***}$ | 12.022 | $0.0004^{***}$ |
| | | [0.0001] | [0.0036] | [0.0035] | [0.0000] | [7.9277] | [0.0000] |
| | With control | 0.0002 | $0.0790^{***}$ | $0.9135^{***}$ | $-0.0145^{***}$ | $1.014^{**}$ | $0.0002^{***}$ |
| | | [0.0001] | [0.0035] | [0.0035] | [0.0051] | [0.4423] | [0.0000] |
| **Colombia** | Without control | 0.0002 | $0.1484^{***}$ | $0.8269^{***}$ | $0.0020^{*}$ | 42.354 | $0.0002^{***}$ |
| | | [0.0003] | [0.0084] | [0.0124] | [0.0011] | [47.723] | [0.0000] |
| | With control | 0.0002 | $0.1444^{***}$ | $0.8263^{***}$ | $0.0167^{***}$ | 43.895 | $0.0003^{***}$ |
| | | [0.0003] | [0.0097] | [0.0129] | [0.0046] | [35.824] | [0.0000] |
| **Hong Kong** | Without control | $0.0005^{***}$ | $0.0570^{***}$ | $0.9325^{***}$ | 0.0007 | 2.2292 | $0.0001^{***}$ |
| | | [0.0001] | [0.0044] | [0.0053] | [0.0006] | [4.3405] | [0.0000] |
| | With control | 0.0005 | $0.0559^{***}$ | $0.9331^{***}$ | $0.0034^{**}$ | 49.093 | $0.0001^{***}$ |
| | | [0.0001] | [0.0045] | [0.0055] | [0.0015] | [148.55] | [0.0000] |
| **India** | Without control | $0.0007^{***}$ | $0.0503^{***}$ | $0.9007^{***}$ | $0.0004^{***}$ | $4.9999^{**}$ | $0.0000^{*}$ |
| | | [0.0001] | [0.0024] | [0.0053] | [0.0000] | [1.4551] | [0.0000] |
| | With control | 0.0008 | $0.1182^{***}$ | $0.8740^{***}$ | $0.0091^{**}$ | 45.163 | $0.0003^{***}$ |
| | | [0.0001] | [0.0060] | [0.0061] | [0.0044] | [49.087] | [0.0000] |
| **Korea** | Without control | $0.0005^{***}$ | $0.0502^{***}$ | $0.9005^{***}$ | $0.0000^{***}$ | $4.9998^{*}$ | $0.0001^{***}$ |
| | | [0.0001] | [0.0031] | [0.0061] | [0.0000] | [2.6932] | [0.0000] |
| | With control | 0.0004 | $0.0788^{***}$ | $0.9191^{***}$ | -0.0090 | 41.234 | $0.0005^{*}$ |
| | | [0.0001] | [0.0049] | [0.0049] | [0.0055] | [44.82] | [0.0002] |
| **Malaysia** | Without control | 0.0000 | $0.1011^{***}$ | $0.8677^{***}$ | 0.0000 | 7.9257 | $0.0000^{***}$ |
| | | [0.0001] | [0.0082] | [0.0105] | [0.0000] | [11.114] | [0.0000] |
| | With control | 0.0000 | $0.1002^{***}$ | $0.8691^{***}$ | $0.0005^{*}$ | 8.4594 | $0.0000^{***}$ |
| | | [0.0001] | [0.0078] | [0.0107] | [0.0003] | [12.319] | [0.0000] |
| **Philippines** | Without control | -0.0001 | $0.2043^{***}$ | $0.7610^{***}$ | $-0.1735^{***}$ | $12.867^{*}$ | $0.0003^{***}$ |
| | | [0.0002] | [0.0167] | [0.0150] | [0.0651] | [7.5727] | [0.0000] |
| | With control | -0.0001 | $0.2091^{***}$ | $0.7578^{***}$ | $0.0075^{**}$ | 44.293 | $0.0002^{***}$ |
| | | [0.0002] | [0.0176] | [0.0158] | [0.0032] | [53.229] | [0.0000] |
| **South Africa** | Without control | $0.0007^{*}$ | $0.0981^{***}$ | $0.8825^{***}$ | 0.1205 | 1.6959 | $0.0000^{*}$ |
| | | [0.0001] | [0.0071] | [0.0087] | [0.0834] | [1.9817] | [0.0000] |
| | With control | 0.0007 | $0.0988^{***}$ | $0.8810^{***}$ | 0.0030 | 0.0014 | $0.0001^{**}$ |
| | | [0.0001] | [0.0073] | [0.0090] | [0.0014] | [43.927] | [0.0000] |
| **Turkey** | Without control | 0.0008 | $0.1351^{***}$ | 0.0001 | $0.0569^{***}$ | $4.9255^{**}$ | $-0.0108^{***}$ |
| | | [0.0012] | [0.0355] | [0.0070] | [0.0023] | [0.4421] | [0.0004] |
| | With control | 0.0020 | $0.1186^{***}$ | $0.0000^{***}$ | $-0.5551^{***}$ | $1.001^{**}$ | $0.0082^{***}$ |
| | | [0.0029] | [0.0319] | [0.0075] | [0.0634] | [0.2214] | [0.0004] |

Note: μ - unconditional mean of stock price returns, α- ARCH term, β - GARCH term, θ - slope coefficient, w - the adjusted beta polynomial weight, and m - long run constant term. The figures in square brackets are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

We examine the impact of GPR shocks on stock market volatility of emerging economies by the statistical significance of the slope coefficient $(\theta)$. Here, the null hypothesis is that the slope coefficient is not significantly different from zero and hence no predictability. The slope coefficient $(\theta)$ in our estimated country-specific GPR-based GARCH-MIDAS-X model is statistically significant to a very large extent. This shows that GPR is a good predictor of stock market volatility. Specifically, it is found to be significantly positive in some cases (Argentina, Colombia, India, Korea, Malaysia, Turkey), significantly negative in some other cases (Brazil, China, and Philippines), and insignificant in other cases (Hong Kong and South Africa). This outcome further attests to the inherent heterogeneity in the estimates and by extension reinforces the need for distinct analyses when modelling GPR-Stock market volatility nexus. The positive relationship found in more than half of the countries implies that higher GPR values in the current month have the tendency to raise stock market volatility (or put more succinctly, stock market risk) in following month. Thus, to make an informed investment decisions, investors can exploit the information provided in our results. That is, when the geopolitical crisis is on the high, the volatility in the market will follow suit, and this might not be the best time to invest, as investors view the future profits and dividend streams to be less than before the crisis caused by geopolitical risk (see also, Homan, 2006). This evidence is similar to those from recent studies such as Hoque and Zaidi (2020) and Smales (2021) notwithstanding the differences in methodology and data proxy, scope and frequency. This outcome suggests that geopolitical risk heightens stock market volatility in emerging economies (being the focus of our study) like it does in developed economies (being the focus of related studies such as Hoque and Zaidi (2020) and Smales (2021)). The negative and insignificant results suggest that higher GPR values do not seem to raise stock market volatility. The latter is an indication that investors in the affected countries seem more confident in the market and do not take panic investment decisions in response to a higher incidence of geopolitical risks.

The role of global economic uncertainty is examined by introducing control variables in the model. As may be observed from Table 4, the models with control variables tend to produce slope coefficient $(\theta)$ higher in magnitude and/or significance than the slope coefficient produced by the models without control variables. For example, the significance of the relevant slope coefficient improves after accounting for control variables in the case of Brazil, Colombia, Hong Kong, and Malaysia. While the significance reduces for India, Philippines and Turkey, it remains unchanged for Argentina, China and South Africa. This suggests the sensitivity of the original

GARCH-MIDAS-GPR model to additional predictors and accounting for them is crucial to avoid misleading outcomes.

Furthermore, we examine the out-of-sample forecast performance of our proposed country-specific GPR-based GARCH-MIDAS-X model by comparing the model with the benchmark (GARCH-MIDAS) model that excludes the GPR measure using the modified Diebold and Mariano test. The result is presented in Table 5. This test is executed as per Harvey, Leybourne, and Newbold (1997) to circumvent the assumption of zero covariance at 'unobserved' lags. Thus, we report both the test statistics and the corresponding p-values. For our forecast performance evaluation, the decision criterion is that, if the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical.

From our out-of-sample forecast result (in Table 5), we find that country-specific geopolitical risk is a good out-of-sample predictor of stock market volatility. This result is consistent across the alternative forecast horizons raging from short term, medium term to long term. Using the out-of-sample R-squared (OOS $R^2$) test proposed by Welch and Goyal (2008) and Campbell and Thompson (2008) for robustness, we further establish the superiority of the GPR-based GARCH-MIDAS (using the country-specific GPR data) over the RV-based variant (see Table A1 in the appendix). Note: The OOS $R^2$ test is computed as $1-(RMSE_{GPR}/RMSE_{RV})$ where $RMSE_{GPR}$ and $RMSE_{RV}$ denote the root mean squared error for the GPR-based GARCH-MIDAS and the RV-based GARCH-MIDAS, respectively. Thus, for the former to outperform the latter, the value of the OOS $R^2$ statistic must be positive while the converse holds if the statistic is negative.

As shown in Table A1, we find that virtually all the statistics are positive indicating preference for the GPR-based GARCH-MIDAS over the alternative model. Thus, our conclusion is not sensitive to the choice of forecast evaluation measure. This evidence further reinforces the outcome from studies on developed economies by Hoque and Zaidi (2020), Salisu et al. (2021) and Smales (2021). Thus, regardless of whether the country is developed or emerging, including the GPR data in the predictive model of stock market volatility improves the forecast outcomes.

**Table 5: Out-of-Sample Forecast Evaluation of Country-Specific GPR for Stock Returns using the Modified Diebold and Mariano test**

| | | Out-of-Sample | | | |
|---|---|---|---|---|---|
| | | h=10 | h=30 | h=60 | h=180 |
| **Argentina** | Without control | -4.4377*** | -3.0900*** | -2.3881** | -1.6448 |
| | With control | -8.6147*** | -5.7990*** | -4.2873*** | -2.6964*** |
| **Brazil** | Without control | -4.3923*** | -3.5811*** | -3.3147*** | -3.2027*** |
| | With control | -4.9818*** | -3.2126*** | -2.7489*** | -2.3182** |
| **China** | Without control | -6.2077*** | -3.9046*** | -2.9496*** | -1.8574* |
| | With control | 13.8955*** | 8.26104*** | 5.9536*** | 3.4281*** |
| **Colombia** | Without control | -3.8409*** | -3.2447*** | -3.0325*** | -3.1145*** |
| | With control | -2.2250** | -2.3848** | -2.2942** | -2.5249*** |
| **Hong Kong** | Without control | -3.2494*** | -1.9818** | -1.5768 | -1.1429 |
| | With control | -2.9699*** | -1.8123* | -1.4432 | -1.0475 |
| **India** | Without control | -7.2670*** | -5.5181*** | -4.8489*** | -3.5078*** |
| | With control | -4.5254*** | -3.6072*** | -3.3353*** | -2.6105*** |
| **Korea** | Without control | -9.6972*** | -6.0154*** | -4.4209*** | -2.6090*** |
| | With control | -9.8158*** | -6.0905*** | -4.4770*** | -2.6418*** |
| **Malaysia** | Without control | -7.1487*** | -4.7543*** | -4.2713*** | -3.9724*** |
| | With control | 27.6612*** | 16.7925*** | 12.1496*** | 7.9655*** |
| **Philippines** | Without control | -1.6628* | -1.5054 | -1.4188 | -2.5615*** |
| | With control | -2.1880** | -1.9696** | -1.8331** | -1.5119 |
| **South Africa** | Without control | -5.3669*** | -3.9708*** | -3.716*** | -7.2829*** |
| | With control | -3.7554*** | -2.8207*** | -2.6662*** | -5.6387*** |
| **Turkey** | Without control | -2.5249*** | -2.5275*** | -2.5346*** | -2.5648*** |
| | With control | -2.5248*** | -2.5275*** | -2.5345*** | -2.5645*** |

Note: Here, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. Also, ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

## 5.2 Stock market volatility and (Aggregate) global geopolitical risk

Note that the previous results only capture the country-specific geopolitical risk indices. We further examine the relationship using the global geopolitical risk index. The predictability and out-of-sample forecast results are presented in Tables 7 and 8, respectively. From Table 7, the results show that the stock market of emerging markets has temporary volatility persistence. This is apparent as the sum of ARCH term ($\alpha$) and GARCH term ($\beta$) for all the emerging countries is less than unity. This implies that effect of shocks on these stock markets is not permanent. The predictability measure, as indicated by the slope coefficient ($\theta$), reveals that geopolitical risk is a good predictor of stock market volatility in emerging countries. The sign is positive suggesting that higher values of geopolitical risk can heighten the stock market risk. In other words, increasing incidence of the components of geopolitical risk such as war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, and escalation of war, terror acts may give rise to stock market volatility through panic trading. This evidence is consistent for virtually all the emerging countries considered, with the exception of Philippines and South Africa. For these two countries, their result does not change even after accounting for the role of global economic factors such as oil market uncertainty and global economic policy uncertainty. However, for all other countries, the significant role of global economic factors is upheld as the size and/or significance is higher under the global-GPR augmented GARCH-MIDAS (GARCH-MIDAS-GGPR) model with control variables compared with the model without control variables. Hence, to a large extent, the result on the role of global economic factors supports findings from the previous studies magnifying the effect of oil market uncertainty and global economic policy uncertainty on financial market performance (see for example, Alqahtani et al., 2020; Lin and Su, 2020; Yang et al., 2021).

The result for the out-of-sample forecast performance based on the modified Diebold and Mariano test is presented in Table 8. The result shows that the out-of-sample forecast performance of global geopolitical risk is not different from that of the country-specific GPR. This is apparent as the GARCH-MIDAS model with the global geopolitical risk outperforms the conventional GARCH-MIDAS with the realized volatility in predicting stock market volatility of emerging markets. Using the out-of-sample R-squared (OOS R2) test proposed by Welch and Goyal (2008) and Campbell and Thompson (2008) for robustness, we further establish the superiority of the GPR-based GARCH-MIDAS (using the global GPR data) over the RV-based variant (see Table A2 in the appendix). This outcome further strengthens the need to account for systematic risks such as those associated with geopolitical factors in the valuation of stocks. This result is consistent under the short horizon (h=10), short to medium horizon (h=30; h=60), and long horizon (h=180).

**Table 6: Predictive Power of (Global) Geopolitical Risk for Stock Returns**

| | | $\mu$ | $\alpha$ | $\beta$ | $\theta$ | $w$ | $m$ |
|---|---|---|---|---|---|---|---|
| **Argentina** | Without control | 0.0011*** | 0.1725*** | 0.7939*** | 0.0001** | 24.668 | 0.0005*** |
| | | [0.0002] | [0.0028] | [0.0065] | [0.0000] | [32.418] | [0.0000] |
| | With control | 0.0012*** | 0.1706*** | 0.7799*** | 0.0266*** | 44.729 | 0.0006*** |
| | | [0.0002] | [0.0037] | [0.0073] | [0.0039] | [37.117] | [0.0000] |
| **Brazil** | Without control | 0.0007*** | 0.0502*** | 0.9005*** | 0.0001*** | 5.0004 | 0.0001*** |
| | | [0.0002] | [0.0036] | [0.0082] | [0.0000] | [4.0981] | [0.0000] |
| | With control | 0.0007 | 0.0785*** | 0.8945*** | 0.0046** | 13.106 | 0.0002*** |
| | | [0.0002] | [0.0060] | [0.0084] | [0.0022] | [24.705] | [0.0000] |
| **China** | Without control | 0.0001 | 0.0568*** | 0.9340*** | -0.0009*** | 2.9905*** | 0.0011*** |
| | | [0.0002] | [0.0043] | [0.0046] | [0.0002] | [0.6300] | [0.0002] |
| | With control | 0.0001 | 0.0557*** | 0.9363*** | -0.0089** | 8.6555 | 0.0002*** |
| | | [0.0002] | [0.0040] | [0.0043] | [0.0050] | [9.2908] | [0.0000] |
| **Colombia** | Without control | 0.0007 | 0.1865*** | 0.7769*** | -0.0012* | 28.207* | 0.0015*** |
| | | [0.0004] | [0.0125] | [0.0219] | [0.0004] | [14.643] | [0.0005] |
| | With control | 0.0008** | 0.2024*** | 0.7613*** | 0.0143 | 22.927 | 0.0002*** |
| | | [0.0003] | [0.0131] | [0.0212] | [0.0115] | [56.797] | [0.0000] |
| **Hong Kong** | Without control | 0.0004*** | 0.0636*** | 0.9243*** | -0.0002*** | 4.9989** | 0.0004*** |
| | | [0.0001] | [0.0051] | [0.0062] | [0.0001] | [2.5454] | [0.0001] |
| | With control | 0.0004*** | 0.0629*** | 0.9253*** | 0.0020 | 27.605 | 0.0001*** |
| | | [0.0001] | [0.0049] | [0.0059] | [0.0025] | [102.77] | [0.0000] |
| **India** | Without control | 0.0008*** | 0.0502*** | 0.9005*** | 0.00003** | 5.0002 | 0.0000*** |
| | | [0.0001] | [0.0025] | [0.0052] | [0.0000] | [5.5639] | [0.0000] |
| | With control | 0.0009 | 0.1097*** | 0.8833*** | -0.0130** | 42.645 | 0.0003*** |
| | | [0.0001] | [0.0062] | [0.0063] | [0.0064] | [43.356] | [0.0001] |
| **Korea** | Without control | -0.0007 | 0.0533** | 0.9007*** | 0.0408*** | 5.0096*** | -0.0333*** |
| | | [0.0004] | [0.0225] | [0.0435] | [0.0053] | [0.2682] | [0.0043] |
| | With control | 0.0004*** | 0.0849*** | 0.8986*** | 0.0225*** | 1.0353*** | 0.0001*** |
| | | [0.0001] | [0.0064] | [0.0072] | [0.0063] | [0.2149] | [0.0002] |
| **Malaysia** | Without control | 0.00002 | 0.0500*** | 0.8474*** | -0.0106* | 4.7841** | 0.0113 * |
| | | [0.0003] | [0.0196] | [0.0196] | [0.0062] | [2.0592] | [0.0066] |
| | With control | 0.0000 | 0.0500*** | 0.9000*** | 0.0998*** | 5*** | -0.0001*** |
| | | [0.0001] | [0.0137] | [0.0262] | [0.0154] | [0.2677] | [0.0000] |
| **Philippines** | Without control | -0.0002 | 0.0502*** | 0.9005*** | -0.0007 | 4.9999 | 0.0008* |
| | | [0.0003] | [0.0058] | [0.0138] | [0.0004] | [4.0905] | [0.0005] |
| | With control | -0.0001 | 0.1692*** | 0.7888*** | 0.0028 | 36.676 | 0.0002*** |
| | | [0.0003] | [0.0196] | [0.0190] | [0.0045] | [236.75] | [0.0000] |
| **South Africa** | Without control | 0.0005*** | 0.0502*** | 0.9005*** | 0.00001 | 4.9999 | 0.00009 *** |
| | | [0.0001] | [0.0038] | [0.0090] | [0.0000] | [6.7691] | [0.0000] |
| | With control | 0.0006 | 0.1008*** | 0.8838*** | 0.0024 | 23.298 | 0.0001** |
| | | [0.0001] | [0.0075] | [0.0088] | [0.0021] | [60.39] | [0.0000] |
| **Turkey** | Without control | 0.0008 | 0.0910*** | 0.0002 | -0.0620*** | 1.34 *** | 0.0653*** |
| | | [0.0013] | [0.0182] | [0.0122] | [0.0012] | [0.0419] | [0.001] |
| | With control | -0.0037*** | 0.0901*** | 0.8798 *** | -2.8592*** | 4.9152** | 0.0366*** |
| | | [0.0007] | [0.0142] | [0.0115] | [0.9980] | [2.1075] | [0.0123] |

Note: μ - unconditional mean of stock price returns, α- ARCH term, β - GARCH term, θ - slope coefficient, w - the adjusted beta polynomial weight, and m - long run constant term. The figures in square brackets are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

**Table 7: Out-of-Sample Forecast Evaluation of Global GPR for Stock Returns using the Modified Diebold and Mariano test**

| | | Out-of-Sample | | | |
|---|---|---|---|---|---|
| | | h=10 | h=30 | h=60 | h=180 |
| **Argentina** | Without control | $-3.9429^{***}$ | $-2.8628^{***}$ | $-2.2547^{**}$ | -1.5950 |
| | With control | $-4.7983^{***}$ | $-3.3632^{***}$ | $-2.6163^{***}$ | $-1.8190^{*}$ |
| **Brazil** | Without control | $-4.0248^{***}$ | $-2.6191^{***}$ | $-2.2616^{**}$ | $-1.9564^{*}$ |
| | With control | $-2.0688^{**}$ | $-1.7866^{*}$ | $-1.7055^{*}$ | $-1.7131^{*}$ |
| **China** | Without control | $-3.8329^{***}$ | $-2.5343^{***}$ | $-1.9810^{**}$ | -1.2582 |
| | With control | $-2.0933^{**}$ | -1.5705 | -1.4699 | -1.1014 |
| **Colombia** | Without control | $-2.0312^{**}$ | $-1.7685^{*}$ | -1.5792 | -1.5231 |
| | With control | $-2.1408^{**}$ | $-1.9564^{**}$ | $-1.6863^{*}$ | -1.6054 |
| **Hong Kong** | Without control | $-3.5041^{***}$ | $-2.1351^{**}$ | $-1.6966^{*}$ | -1.2269 |
| | With control | $-4.6204^{***}$ | $-3.1765^{***}$ | $-2.4299^{**}$ | -1.5680 |
| **India** | Without control | $-9.4545^{***}$ | $-6.8393^{***}$ | $-5.9197^{***}$ | $-4.2133^{***}$ |
| | With control | $-4.8839^{***}$ | $-3.9137^{***}$ | $-3.7102^{***}$ | $-3.4608^{***}$ |
| **Korea** | Without control | $-10.1840^{***}$ | $-6.2533^{***}$ | $-4.5850^{***}$ | $-2.7028^{***}$ |
| | With control | $-6.5248^{***}$ | $-4.0409^{***}$ | $-2.9682^{***}$ | $-1.7776^{*}$ |
| **Malaysia** | Without control | $31.1654^{***}$ | $17.9806^{***}$ | $13.0137^{***}$ | $8.5353^{***}$ |
| | With control | $-2.5654^{***}$ | $-1.8626^{*}$ | -1.6242 | -1.3254 |
| **Philippines** | Without control | $-1.6756^{*}$ | -1.5649 | -1.4813 | $-3.4034^{***}$ |
| | With control | -1.6419 | -1.4017 | -1.2983 | -1.4667 |
| **South Africa** | Without control | $-9.4263^{***}$ | $-6.0005^{***}$ | $-4.9143^{***}$ | $-3.9586^{***}$ |
| | With control | $-4.7242^{***}$ | $-3.5363^{***}$ | $-3.3378^{***}$ | $-7.1566^{****}$ |
| **Turkey** | Without control | $-2.5260^{***}$ | $-2.5286^{***}$ | $-2.5357^{***}$ | $-2.5654^{***}$ |
| | With control | $-2.5251^{***}$ | $-2.5277^{***}$ | $-2.5347^{***}$ | $-2.5647^{***}$ |

Note: Here, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. Also, ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

## 5.3 Stock market volatility and (Disaggregated) global GPR

Furthermore, we examine the predictability of disaggregated global geopolitical risks (act-related GPR and threat-related GPR) for stock market volatility of emerging markets. Similar to the country-specific and (aggregate) global GPR models, we present the predictability and the out-of-sample forecast performance results for the global GPR Act (GGPRA) and the global GPR Threat (GGPRT). The predictability results for GGPRT and GGPRA are presented in Tables 9 and 10, respectively; while the out-of-sample forecast evaluation results for GGPRT and GGPRA are presented in Tables 11 and 12, respectively.

From Tables 9 and 10, we find that the emerging markets have temporary volatility persistence whether the global GPR is act-induced or threat-related. The volatility persistence is based on the sum of ARCH term ($\alpha$) and GARCH term ($\beta$) which is less than one for all the emerging markets under the two (GPR-based) GARCH-MIDAS models. This implies that effect of shocks on these markets are transient. The slope coefficient, $(\theta)$, which measures the impact of the predictor series, reveals that both the act-related and threat-related GPR indices are good predictors of stock market volatility in emerging markets. While this result is consistent across all the emerging countries considered for the act-related GPR data (see Table 10), the volatility of stock markets in Brazil and South Africa does not seem to respond to GPR threat (see Table 9). This suggests that act-related GPR is a better predictor of stock market volatility in emerging markets than threat-related GPR, on average. This result is similar to the finding by Mei et al. (2020) which shows that GPRA contributes more to the long-term oil volatility forecasting compared with GPRT. In terms of the direction of relationship between the GPR indices and stock market volatility, our earlier discussion on the economic meaning of both the positive and negative signs on the slope coefficient, $(\theta)$, suffices to avoid repetition.

The results for the out-of-sample forecast performance comparing the GPRT and GPRA augmented GARCH-MIDAS models with the conventional GARCH-MIDAS (GARCH-MIDAS-RV) are presented in Tables 11 and 12, respectively. The result shows that the out-of-sample forecast performance of the act-related and threat-related global geopolitical risks is not different from that of the country-specific and aggregate global GPR indices. The results are also validated by the out-of-sample R-squared (OOS R2) test proposed by Welch and Goyal (2008) and Campbell and Thompson (2008) (see Tables A3 and A4 in the appendix) where the statistics are positive and less than one indicating the superior performance of a GPR-based GARCH-MIDAS (whether GPR act or GPR threat) over the variant with Realized Volatility. In other words, both the act- and threat-related global geopolitical risks offer improved out-of-sample predictability of stock market volatility in emerging markets similar to studies on developed economies by Hoque and Zaidi (2020), Salisu et al. (2021) and Smales (2021).

**Table 8: Predictive Power of Geopolitical risk for Stock Returns (Global GPR Threat)**

| | | $\mu$ | $\alpha$ | $\beta$ | $\theta$ | $w$ | $m$ |
|---|---|---|---|---|---|---|---|
| **Argentina** | Without control | 0.0011*** | 0.1770*** | 0.7906*** | 0.0003*** | 13.299 | 0.0003*** |
| | | [0.0002] | [0.0030] | [0.0068] | [0.0001] | [10.32] | [0.0001] |
| | With control | 0.0011*** | 0.1748*** | 0.7874*** | 0.0234*** | 16.443 | 0.0006*** |
| | | [0.0002] | [0.0035] | [0.0071] | [0.0053] | [10.034] | [0.0000] |
| **Brazil** | Without control | 0.0007*** | 0.0840*** | 0.8862*** | 0.0001 | 1.0676 | 0.0001* |
| | | [0.0002] | [0.0066] | [0.0093] | [0.0000] | [1.358] | [0.0000] |
| | With control | 0.0007 | 0.0844*** | 0.8858*** | -0.0006 | 22.138 | 0.0002*** |
| | | [0.0002] | [0.0066] | [0.0095] | [0.0024] | [342.64] | [0.0000] |
| **China** | Without control | 0.0027*** | 0.0503*** | 0.9004*** | 0.0300*** | 4.9992*** | -0.0187*** |
| | | [0.0008] | [0.0193] | [0.0477] | [0.0051] | [0.0506] | [0.0032] |
| | With control | 0.0002 | 0.0775*** | 0.9160*** | -0.0108** | 3.605 | 0.0003*** |
| | | [0.0001] | [0.0036] | [0.0035] | [0.0054] | [3.4979] | [0.0000] |
| **Colombia** | Without control | 0.0002 | 0.1477*** | 0.8215*** | -0.0004*** | 48.61*** | 0.0008*** |
| | | [0.0003] | [0.0117] | [0.0154] | [0.0001] | [15.132] | [0.0001] |
| | With control | 0.0007** | 0.1811*** | 0.7833*** | 0.0783 | 1.0622 | 0.0001*** |
| | | [0.0004] | [0.0132] | [0.0213] | [0.0267] | [1.8622] | [0.0003] |
| **Hong Kong** | Without control | 0.0015*** | 0.0520*** | 0.9005*** | 0.0107*** | 5.0014*** | -0.0082*** |
| | | [0.0004] | [0.0051] | [0.0098] | [0.0000] | [0.0062] | [0.0000] |
| | With control | 0.0003 | 0.0485*** | 0.9334*** | 0.0141* | 1.0586*** | 0.0001*** |
| | | [0.0002] | [0.0055] | [0.0077] | [0.0063] | [0.3992] | [0.0000] |
| **India** | Without control | 0.0008*** | 0.119*** | 0.8715*** | -0.0002*** | 9.5668*** | 0.0005*** |
| | | [0.0001] | [0.0063] | [0.0065] | [0.0000] | [3.4042] | [0.0001] |
| | With control | 0.0010*** | 0.0503*** | 0.9005*** | 0.0108*** | 4.9999*** | 0.00007*** |
| | | [0.0000] | [0.0015] | [0.0028] | [0.0003] | [0.4621] | [0.0000] |
| **Korea** | Without control | 0.0004 | 0.0503** | 0.9007*** | 0.00007*** | 4.9997** | -0.00002 |
| | | [0.0001] | [0.0035] | [0.0068] | [0.0000] | [2.412] | [0.0000] |
| | With control | -0.0026*** | 0.0330*** | 0.8998*** | 0.0335*** | 5.3062*** | 0.0002*** |
| | | [0.0001] | [0.0013] | [0.0038] | [0.0007] | [0.2438] | [0.0000] |
| **Malaysia** | Without control | 0.0011 | 0.0660*** | 0.9006*** | 0.0130*** | 5.0151*** | -0.0121*** |
| | | [0.0001] | [0.0208] | [0.0260] | [0.0033] | [0.0275] | [0.0030] |
| | With control | 0.0000 | 0.1058*** | 0.8782*** | 0.0063** | 3.5411 | 0.00002** |
| | | [0.0001] | [0.0118] | [0.0135] | [0.0029] | [4.4862] | [0.0000] |
| **Philippines** | Without control | -0.0002 | 0.0503*** | 0.9006*** | 0.0002** | 4.9998 | -0.0001 |
| | | [0.0003] | [0.0054] | [0.0137] | [0.0001] | [3.8787] | [0.0001] |
| | With control | -0.0001 | 0.1729*** | 0.7853*** | 0.0261** | 1.0747 | 0.0001* |
| | | [0.0003] | [0.0198] | [0.0188] | [0.0111] | [1.8928] | [0.0000] |
| **South Africa** | Without control | 0.0006*** | 0.1075*** | 0.8923*** | 0.0253 | 8.1707** | -0.0146 |
| | | [0.0001] | [0.0076] | [0.0076] | [0.0311] | [3.8827] | [0.0187] |
| | With control | 0.0006*** | 0.0961*** | 0.8909*** | 0.0013 | 16.431 | 0.0001*** |
| | | [0.0001] | [0.0076] | [0.0087] | [0.0026] | [80.439] | [0.0000] |
| **Turkey** | Without control | 0.0009 | 0.0907*** | 3.5351e-07 | -0.0339*** | 2.475 *** | 0.0406*** |
| | | [0.0008] | [0.0179] | [0.0126] | [0.0006] | [0.0117] | [0.0008] |
| | With control | -0.0014 | 0.0911*** | 0.8740 *** | -2.6947*** | 4.8223*** | 0.0305*** |
| | | [0.0014] | [0.0118] | [0.0097] | [0.7880] | [0.2655] | [0.0089] |

Note: μ - unconditional mean of stock price returns, α- ARCH term, β - GARCH term, θ - slope coefficient, w - the adjusted beta polynomial weight, and m - long run constant term. The figures in square brackets are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

**Table 9: Predictive Power of Geopolitical Risk for Stock Returns (Global GPR Act)**

| | | $\mu$ | $\alpha$ | $\beta$ | $\theta$ | $w$ | $m$ |
|---|---|---|---|---|---|---|---|
| **Argentina** | Without control | 0.0011*** | 0.1649*** | 0.8347*** | 0.0497* | 4.5762*** | -0.0325* |
| | | [0.0002] | [0.0026] | [0.0026] | [0.0282] | [0.4728] | [0.0184] |
| | With control | 0.0013*** | 0.1949*** | 0.7464*** | 0.0255*** | 47.92 | 0.0005*** |
| | | [0.0002] | [0.0040] | [0.0087] | [0.0040] | [37.425] | [0.0000] |
| **Brazil** | Without control | 0.0010 | 0.0536*** | 0.9005*** | 0.0084*** | 5.0122*** | -0.0053* |
| | | [0.0007] | [0.0052] | [0.0106] | [0.0000] | [0.4584] | [0.0000] |
| | With control | 0.0004 | 0.0913*** | 0.8804*** | 0.0060 | 38.365 | 0.0002*** |
| | | [0.0002] | [0.0079] | [0.0106] | [0.0034] | [92.039] | [0.0000] |
| **China** | Without control | 0.0002 | 0.0666*** | 0.9272*** | -0.0001** | 4.9989*** | 0.0003*** |
| | | [0.0001] | [0.0035] | [0.0034] | [0.0000] | [3.4716] | [0.0001] |
| | With control | 0.0002 | 0.0745*** | 0.9181*** | -0.0138** | 4.0584 | 0.0002*** |
| | | [0.0001] | [0.0035] | [0.0035] | [0.0061] | [2.7916] | [0.0000] |
| **Colombia** | Without control | 0.0007* | 0.1842*** | 0.7805*** | -0.0008** | 3.9394 | 0.0011** |
| | | [0.0004] | [0.0138] | [0.0218] | [0.0004] | [4.2513] | [0.0004] |
| | With control | 0.0007** | 0.1829*** | 0.7774*** | 0.0151 | 49.63 | 0.0002*** |
| | | [0.0004] | [0.0134] | [0.0220] | [0.0070] | [118.44] | [0.0000] |
| **Hong Kong** | Without control | 0.0004*** | 0.0571*** | 0.9117*** | -0.0001** | 5.0001*** | 0.0002*** |
| | | [0.0002] | [0.0046] | [0.0073] | [0.0000] | [3.0599] | [0.0000] |
| | With control | 0.0004*** | 0.0554*** | 0.9344*** | 0.0034** | 44.643 | 0.0001*** |
| | | [0.0002] | [0.0044] | [0.0053] | [0.0016] | [110.26] | [0.0000] |
| **India** | Without control | 0.0008*** | 0.1052*** | 0.8768*** | 0.0001** | 1.0351** | 0.00009* |
| | | [0.0002] | [0.0072] | [0.0080] | [0.0000] | [0.4784] | [0.0001] |
| | With control | 0.0008*** | 0.0901*** | 0.8921*** | 0.0118*** | 26.994 | 0.0002*** |
| | | [0.0002] | [0.0075] | [0.0084] | [0.0047] | [25.9] | [0.0000] |
| **Korea** | Without control | 0.0001*** | 0.0501*** | 0.9003*** | 0.0537*** | 5.0001*** | -0.0380*** |
| | | [0.0011] | [0.0123] | [0.0110] | [0.0112] | [0.3609] | [0.0079] |
| | With control | 0.0004*** | 0.0852*** | 0.8900*** | 0.0285*** | 1.1016*** | 0.0001*** |
| | | [0.0001] | [0.0068] | [0.0085] | [0.0052] | [0.1566] | [0.0000] |
| **Malaysia** | Without control | -0.00006 | 0.1604*** | 0.6233*** | -0.0002 | 9.2156 | 0.0001* |
| | | [0.0003] | [0.0538] | [0.1242] | [0.0001] | [7.9783] | [0.0000] |
| | With control | 0.0003 | 0.0500* | 0.9000*** | 0.0995*** | 5*** | 0.0002*** |
| | | [0.0008] | [0.0256] | [0.0290] | [0.0391] | [0.4616] | [0.0000] |
| **Philippines** | Without control | 0.0008 | 0.1977*** | 0.7711*** | -0.0067 | 3.2586 | 0.0057 |
| | | [0.0013] | [0.0478] | [0.0326] | [0.0206] | [49.051] | [0.0273] |
| | With control | -0.0002 | 0.1998*** | 0.7608*** | 0.0078* | 49.804 | 0.0002* |
| | | [0.0002] | [0.0195] | [0.0184] | [0.0042] | [130.3] | [0.0000] |
| **South Africa** | Without control | 0.0003*** | 0.0503*** | 0.9005*** | 1.59e-05* | 5.0003 | 9.55e-05 |
| | | [0.0001] | [0.0040] | [0.0095] | [0.0000] | [5.4547] | [0.0000] |
| | With control | 0.0006*** | 0.0967*** | 0.8874*** | 0.0043** | 42.969 | 0.0001*** |
| | | [0.0001] | [0.0077] | [0.0091] | [0.0020] | [67.115] | [0.0000] |
| **Turkey** | Without control | 0.0005* | 0.1019*** | 0.8089 | -0.0004*** | 1.5182*** | 0.0005*** |
| | | [0.0002] | [0.0143] | [0.0272] | [0.0001] | [0.3715] | [0.0001] |
| | With control | 0.0005*** | 0.0831*** | 0.8371*** | 0.0034*** | 44.187 | 0.0001*** |
| | | [0.0003] | [0.0136] | [0.0292] | [0.0014] | [87.034] | [0.0000] |

Note: μ - unconditional mean of stock price returns, α- ARCH term, β - GARCH term, θ - slope coefficient, w - the adjusted beta polynomial weight, and m - long run constant term. The figures in square brackets are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

**Table 10: Out-of-Sample Forecast Evaluation of Global GPR Threat for Stock Returns using the Modified Diebold and Mariano test**

| | | Out-of-Sample | | | |
|---|---|---|---|---|---|
| | | h=10 | h=30 | h=60 | h=180 |
| **Argentina** | Without control | -2.8235*** | -2.0512** | -1.6052 | -1.1356 |
| | With control | -2.6183*** | -1.9107* | -1.4974 | -1.0595 |
| **Brazil** | Without control | -3.5574*** | -2.4677*** | -2.2279** | -2.0673** |
| | With control | -1.9716** | -1.6988* | -1.6171 | -1.6562* |
| **China** | Without control | -10.3335*** | -6.7852*** | -5.3876*** | -3.6466*** |
| | With control | 13.4747*** | 7.8266*** | 5.6203 | 3.4730*** |
| **Colombia** | Without control | -0.7842 | -0.8507 | -0.7052 | -0.6615 |
| | With control | -1.5691 | -1.8511* | -1.5517 | -1.4474 |
| **Hong Kong** | Without control | -2.9114*** | -2.3803** | -2.4678*** | -1.8278** |
| | With control | -2.4894** | -2.0526** | -2.0232** | -1.3415 |
| **India** | Without control | -9.7150*** | -6.9672*** | -5.9777*** | -4.1903*** |
| | With control | -5.3035*** | -4.7001*** | -4.3309*** | -3.8951*** |
| **Korea** | Without control | -2.2765** | -1.5099 | -1.1565 | -0.8046 |
| | With control | -2.9632*** | -1.9688** | -1.5125 | -1.0538 |
| **Malaysia** | Without control | -2.1122** | -1.7250* | -1.5064 | -1.3032 |
| | With control | -2.5642** | -1.8808* | -1.6351 | -1.3416 |
| **Philippines** | Without control | -1.9894** | -1.7867* | -1.7074* | -2.3916* |
| | With control | -3.0952*** | -2.5623*** | -2.1266** | -1.4259 |
| **South Africa** | Without control | -5.1705*** | -3.8424*** | -3.5994*** | -6.8238*** |
| | With control | -4.6222*** | -3.4583*** | -3.2685*** | -7.211*** |
| **Turkey** | Without control | -2.5252*** | -2.5287*** | -2.5357*** | -2.5653*** |
| | With control | -2.5251*** | -2.5277*** | -2.5348*** | -2.5650*** |

Note: Here, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. Also, ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

**Table 11: Out-of-Sample Forecast Evaluation of Global GPR Act for Stock Returns using the Modified Diebold and Mariano test**

| | | Out-of-Sample | | | |
|---|---|---|---|---|---|
| | | h=10 | h=30 | h=60 | h=180 |
| **Argentina** | Without control | -2.3592** | -1.7507* | -1.3781 | -1.0324 |
| | With control | -1.9990** | -1.4847 | -1.1734 | -0.8781 |
| **Brazil** | Without control | -1.6525 | -1.3162 | -1.2039 | -1.1074 |
| | With control | -2.0688** | -1.7866* | -1.7056* | -0.8781 |
| **China** | Without control | -9.3525*** | -6.0946*** | -4.8129*** | -3.2029*** |
| | With control | -0.0618 | -0.0455 | -0.0482 | -0.0386 |
| **Colombia** | Without control | -1.9289* | -1.9101* | -1.7349* | -1.6949* |
| | With control | -1.4880 | -1.7755* | -1.4907 | -1.4119 |
| **Hong Kong** | Without control | -2.5056*** | -2.1175** | -1.7568* | -1.0989 |
| | With control | -3.93867*** | -3.4541*** | -3.5758*** | -2.3221** |
| **India** | Without control | -8.9056*** | -6.3855*** | -5.5203*** | -3.8996*** |
| | With control | -1.9253* | -1.6243 | -1.5264 | -1.0917 |
| **Korea** | Without control | -2.2701** | -1.5079 | -1.1582 | -0.8061 |
| | With control | -2.29837** | -1.5257 | -1.1757 | -0.8209 |
| **Malaysia** | Without control | 7.2588*** | 4.4581*** | 3.2039*** | 1.8384* |
| | With control | 18.5293*** | 10.7284*** | 7.6759*** | 4.8412*** |
| **Philippines** | Without control | -3.8732*** | -3.5004*** | -3.3347*** | -4.4002*** |
| | With control | -1.9537* | -1.5857 | -1.4875 | -1.6133 |
| **South Africa** | Without control | -8.9209*** | -5.6633*** | -4.6210*** | -3.6624*** |
| | With control | -4.5023*** | -3.3709*** | -3.1769*** | -6.6502*** |
| **Turkey** | Without control | -2.6239*** | -2.7555*** | -2.4754*** | -1.8686* |
| | With control | -2.5232*** | -2.5257*** | -2.5327*** | -2.5644*** |

Note: Here, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. Also, ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. Without control represents the GARCH-MIDAS X model with relevant GPR variant while with control represents GARCH-MIDAS X model augmented with oil market uncertainty index (OMUI) and global economic policy uncertainty (GEPU).

## 6. Conclusion

In this study, we examine the predictability of geopolitical risk for stock returns volatility in emerging economies using the GARCH-MIDAS approach. Recently, there is a growing body of literature establishing nexus between stock returns and changes in geopolitical risks (see Brounrn and Derwall, 2010; Aslam and Kang, 2015; Antonakakis et al., 2017; Balcilar et al., 2018; Plakandaras et al., 2019; Alqahtani et al., 2020; Baur and Smales, 2020; Zhou et al., 2020; Smales 2021; Yang et al., 2021). Thus, we contribute to this body of literature in three ways. First, we provide evidence for the predictive content of the country-specific and global (aggregate and disaggregated – Act and Threat) GPR for stock market volatility. Second, we account for the role of global economic uncertainty specifically, oil market uncertainty and global economic policy uncertainty. Third, we employ a methodology that accommodates mixed data frequency thereby circumventing information loss or any associated bias. To achieve these, we adopt a predictive model that permits the use of mixed data frequency for greater variability and more robust information. We construct a GARCH-MIDAS-X models where the geopolitical risk indicators (in natural logs) serve as a predictor. The focus of our analysis is the MIDAS slope coefficient ($\theta$) that indicates the predictability of the incorporated exogenous predictor. For the out-of-sample forecast evaluation, we compare the forecasts of our proposed GARCH-MIDAS predictive model (involving GPR - with/without control variables) with that of the conventional GARCH-MIDAS specifications that include realized volatility (GARCH-MIDAS-RV).

There are four prominent conclusions from this study. First, emerging stock market volatility responds more positively to country-specific and global geopolitical risks. This implies that higher geopolitical risks may heighten stock market volatility in emerging markets. Second, accounting for global economic factors tends to enhance the predictability of stock market volatility in emerging economies. Third, country-specific and global geopolitical risks offer improved out-of-sample predictability of stock market volatility in emerging markets. Lastly, the study shows that the act-related GPR is a better predictor of stock market volatility in emerging markets than the threat-related GPR. In sum, regardless of the GPR measure (whether country-specific or global), increased incidence of geopolitical crises has the tendency of causing fear in the stock markets which consequently heightens the market volatility. These findings offer useful pointers to investors particularly in terms of the timing of investment and valuation of stocks to minimize the consequences of geopolitical risk on future returns. From policy perspective, dealing with geopolitical risks is crucial for improved stock market performance since this factor in general impacts negatively on capital flows where risk-averse investors seek safe investments with relatively lower incidence of GPR. Therefore, investors and policy-makers are advised to pay close attention to geopolitical risks and its components (especially Act) while predicting volatility in the stock markets. An interesting area to further advance this study would be to examine the economic significance of including GPR in a predictive model of stock market volatility.

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## Appendix

**Table A1: Out-of-Sample Forecast Evaluation of Country-Specific GPR for Stock Returns using R-test Statistics**

| | h=10 | h=30 | h=60 | h=180 |
|---|---|---|---|---|
| **Argentina** | 0.0025 | 0.0017 | 0.0016 | 0.0024 |
| **Brazil** | 0.0060 | 0.0057 | 0.0057 | 0.0063 |
| **China** | 0.0009 | 0.0011 | 0.0011 | -0.0011 |
| **Colombia** | 0.0374 | 0.0106 | 0.0109 | 0.0097 |
| **Hong Kong** | 0.0086 | 0.0094 | 0.0066 | 0.0046 |
| **India** | 0.0042 | 0.0043 | 0.0046 | 0.0044 |
| **Korea** | 0.0219 | -0.0049 | 0.0207 | 0.0259 |
| **Malaysia** | 0.0008 | 0.0008 | 0.0009 | 0.0006 |
| **Philippines** | 0.0022 | 0.0022 | -0.0002 | 0.0009 |
| **South Africa** | 0.0004 | 0.0004 | 0.0004 | 0.2792 |
| **Turkey** | 0.0221 | 0.0221 | 0.0222 | -0.0743 |

Note: The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. The OOS $R^2$ test is the out-of-sample R-Squared test computed as $1-\left(RMSE_{GPR}/RMSE_{RV}\right)$ where $RMSE_{GPR}$ and $RMSE_{RV}$ denote the root mean squared error for the GPR-based GARCH-MIDAS and the RV-based GARCH-MIDAS, respectively. Thus, for the former to outperform the latter, the value of the OOS $R^2$ statistic must be positive while the converse holds if the statistic is negative.

**Table A2: Out-of-Sample Forecast Evaluation of Global GPR for Stock Returns using R-test Statistics**

| | h=10 | h=30 | h=60 | h=180 |
|---|---|---|---|---|
| **Argentina** | 0.0017 | 0.0008 | -0.0041 | -2.5649 |
| **Brazil** | 0.0172 | 0.0178 | 0.0177 | 0.0171 |
| **China** | -0.0077 | 0.0000 | 0.0000 | 0.0000 |
| **Colombia** | 0.0303 | 0.0302 | 0.0104 | 0.0261 |
| **Hong Kong** | 0.0087 | 0.0129 | 0.0054 | 0.0057 |
| **India** | 0.0046 | 0.0048 | 0.0029 | 0.0009 |
| **Korea** | 0.0301 | 0.0358 | 0.0386 | 0.0401 |
| **Malaysia** | 0.0585 | 0.0585 | 0.0514 | 0.0122 |
| **Philippines** | -0.0031 | -0.0063 | 0.0015 | -0.0047 |
| **South Africa** | 0.0000 | 0.0002 | -0.0132 | 0.0002 |
| **Turkey** | 0.0017 | 0.0008 | -0.0041 | -2.5649 |

Note: The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. The OOS $R^2$ test is the out-of-sample R-Squared test computed as $1-\left(RMSE_{GPR}/RMSE_{RV}\right)$ where $RMSE_{GPR}$ and $RMSE_{RV}$ denote the root mean squared error for the GPR-based GARCH-MIDAS and the RV-based GARCH-MIDAS, respectively. Thus, for the former to outperform the latter, the value of the OOS $R^2$ statistic must be positive while the converse holds if the statistic is negative.

**Table A3: Out-of-Sample Forecast Evaluation of Globak GPR Threat for Stock Returns using R-test Statistics**

| | h=10 | h=30 | h=60 | h=180 |
|---|---|---|---|---|
| **Argentina** | 0.0017 | 0.0008 | 0.0016 | 0.0016 |
| **Brazil** | 0.0046 | 0.0124 | 0.0093 | 0.0108 |
| **China** | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| **Colombia** | 0.0246 | 0.0119 | 0.0117 | 0.0141 |
| **Hong Kong** | 0.0029 | 0.0072 | 0.0064 | 0.0029 |
| **India** | 0.0046 | 0.0047 | 0.0051 | 0.0051 |
| **Korea** | 0.0104 | 0.0013 | 0.0172 | 0.0236 |
| **Malaysia** | 0.0437 | 0.0014 | 0.0012 | 0.0010 |
| **Philippines** | 0.0017 | -0.0043 | 0.0020 | -0.0021 |
| **South Africa** | 0.0002 | 0.0002 | 0.0002 | 0.2271 |
| **Turkey** | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Note: The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. The OOS $R^2$ test is the out-of-sample R-Squared test computed as $1-\left(RMSE_{GPR}/RMSE_{RV}\right)$ where $RMSE_{GPR}$ and $RMSE_{RV}$ denote the root mean squared error for the GPR-based GARCH-MIDAS and the RV-based GARCH-MIDAS, respectively. Thus, for the former to outperform the latter, the value of the OOS $R^2$ statistic must be positive while the converse holds if the statistic is negative.

**Table A4: Out-of-Sample Forecast Evaluation of Global GPR Act for Stock Returns using R-test Statistics**

| | h=10 | h=30 | h=60 | h=180 |
|---|---|---|---|---|
| **Argentina** | 0.0017 | 0.0008 | 0.0016 | 0.0024 |
| **Brazil** | 0.0183 | 0.0166 | 0.0137 | 0.0152 |
| **China** | 0.0140 | 0.0003 | -21.0365 | 0.0002 |
| **Colombia** | 0.0168 | 0.0187 | 0.0163 | 0.0199 |
| **Hong Kong** | 0.0016 | -0.0147 | -0.0146 | -0.0333 |
| **India** | 0.0046 | 0.0047 | 0.0020 | 0.0048 |
| **Korea** | 0.0175 | -20.3626 | 0.0202 | 0.0198 |
| **Malaysia** | 0.0598 | 0.0402 | 0.0003 | -0.0010 |
| **Philippines** | 0.0086 | 0.0019 | 0.0205 | 0.0039 |
| **South Africa** | 0.0000 | 0.0002 | 0.0000 | -0.0117 |
| **Turkey** | 0.0181 | 0.0000 | 0.0000 | 0.0000 |

Note: The test is based on GARCH-MIDAS-RV vs. GARCH-MIDAS-X. The OOS $R^2$ test is the out-of-sample R-Squared test computed as $1-\left(RMSE_{GPR}/RMSE_{RV}\right)$ where $RMSE_{GPR}$ and $RMSE_{RV}$ denote the root mean squared error for the GPR-based GARCH-MIDAS and the RV-based GARCH-MIDAS, respectively. Thus, for the former to outperform the latter, the value of the OOS $R^2$ statistic must be positive while the converse holds if the statistic is negative.