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Afees A. Salisu
University of Ibadan
Juncal Cunado
University of Navarra
Rangan Gupta
University of Pretoria
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Geopolitical Risks and Historical Exchange Rate Volatility of the BRICS

Afees A. Salisu*, Juncal Cuñado** and Rangan Gupta***

Abstract: This paper examines the vulnerability of BRICS exchange rates to geopolitical risks (GPR) using alternative measures ranging from global (historical and recent) GPR data to country-specific GRP data. We construct a GARCH-MIDAS-X model in order to accommodate available data frequencies for relevant series and by extension circumvent information loss and any associated bias. Using the long range data, we find that, on average, the BRICS exchange rates are less vulnerable to geopolitical risks, however, recent (short range) data suggest otherwise. We also find contrasting evidence between the recent global GPR data and the country-specific GPR data implying that the BRICS exchange rates are more vulnerable to global than domestic (country-specific) geopolitical risks in recent times while China seems to be the least vulnerable. The GARCH-MIDAS model that accounts for the GPR data outperforms the benchmark (the conventional GARCH-MIDAS model without the GPR predictor) both for the in-sample and out-of-sample forecasts. We also highlight some similarities in the results of long range GPR and oil price uncertainty and further note the sensitivity of the results to alternative data samples for GPR. Finally, our results have implications for portfolio diversification strategies in the BRICS foreign exchange markets and in particular, we document economic gains of accounting for GPR in the valuation of foreign exchange portfolio.

Keywords: Geopolitical risk; Exchange rate volatility; BRICS; GARCH-MIDAS; Forecast evaluation.

JEL codes: C53; F31; G17.

* Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria. Email: adebare1@yahoo.com.

** University of Navarra, School of Economics, Edificio Amigos, E-31080 Pamplona, Spain. Email: jcunado@unav.es.

*** Department of Economics, University of Pretoria, Pretoria, South Africa. Email: rangan.gupta@up.ac.za.

1. Introduction

Geopolitical risks (GPR), broadly defined as the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations (Caldara and Iacovello, 2019), are considered key determinants of investment decisions and financial market dynamics (Berkman et al., 2011; Pastor and Veronesi, 2012; Huang et al., 2015), and thus, they will certainly exert movements in the exchange rate market, which is the largest and most liquid financial market in the world with around $6.6trn traded per day in 2019 (Bank of International Settlements, BIS, 2019). For example, after the Russian invasion of the Crimea in 2014, the Russian ruble lost half of its value against the dollar within that year, causing an increase in the exchange rate volatility of this currency. Exchange rate volatility has been a topic of interest in the academic literature, since exchange rate volatility is a key feature for option pricing, financial market regulation, investment or hedging decisions (Eun and Resnick, 1988; Hansen and Lunde, 2005; Christoffersen and Diebold, 2006; Fidora et al., 2007; Caporale et al., 2015), so that many empirical attempts to forecast exchange rate volatility are found in the literature (Diebold and Nerlove, 1989; Hansen and Lunde, 2005; Benavides and Capistrán, 2012; Barunik et al., 2016; Rapach and Strauss, 2018).

GPR have been observed to impact stock returns and volatility (Chen and Siems, 2004; Brounen and Derwall, 2010; Chesney et al., 2011; Balcilar et al., 2018; Yang et al., 2021), reduce economic activity (Bloomberg et al., 2004; Cheng and Chiu, 2018), affect Bitcoin price volatility and returns (Aysan et al., 2019), impact exchange rates (Balcilar et al., 2017), gold volatility (Gkillas et al., 2020), and crude oil returns and volatility (Antonakakis et al., 2017). Although GPR will impact exchange rate volatility through all these channels, the study of the impact of GPR on exchange rate volatility is still absent from the literature.

From a theoretical point of view, GPR could affect exchange rate returns and volatility through a number of channels, such as reducing international trade flows (Eckstein and Tsiddon, 2004; Glick and Taylor, 2010; Balcilar et al., 2018; Gupta et al., 2019), through changes in international capital or portfolio flows (Abadie and Gardeazabal, 2008; Cheng and Chiu, 2018; Aysan et al., 2019), or altering the formation of market participants' expectations (Balcilar et al., 2017). Thus, an increase in GPR will be expected to reduce trade flows through increasing the trade costs (Walkenhorst and Dihel, 2002) and decreasing households' investment and consumption of foreign goods. At the same time, under a period of high GPR, investors will direct savings from more exposed countries to other countries, and these movements will impact the exchange rates of these economies. In fact, the impact on exchange rates will depend on each country's exposition to GPR, on whether GPR are country-specific or global, on each country's macroeconomic fundamentals, on the safe haven properties of its currency and on the exchange rate regime in each of the countries. In this context, academic literature has found that foreign capital moves from emerging to developed countries in periods of uncertainty or geopolitical risks (Caldara and Iacovello, 2019), assuming that currencies in developed countries can act as safe havens (Fatum and Yamamoto, 2016) in times of increased risk aversion caused by episodes of GPR, although the impact of these flows on exchange rate volatility is not clear. Caporale et al. (2017), for example, investigate the effects of equity and bond portfolio inflows on exchange rate volatility of several emerging Asian countries and conclude that while equity inflows increase exchange rate volatility, bond inflows decrease it. Furthermore, and when considering emerging economies, exchange rate regimes will also determine the exchange rate vulnerability of each country to GPR (Jeanne and Rose, 2002).

In this context, the objective of this paper is to analyse the relationship between geopolitical risks and exchange rate volatility in BRICS countries. Specifically, it analyses the in-sample and out-of-sample predictability capacity of GPR for exchange rate volatility, while at the same time it studies the vulnerability of each of the BRICS currencies to GPR. This paper contributes to the literature on exchange rate volatility predictability in a number of ways. First, we examine the exchange rate volatility predictability in a sample of emerging countries by focusing on the BRICS (Brazil, Russia, India, China, South Africa) countries. The focus on this group of countries[1] makes the analysis relevant since, first, they are largely affected by foreign investment flows, and second, their exchange rates have been determined by different exchange rate regimes. For example, these countries attracted 20% of the world Foreign Direct Investment (FDI) inflows and received 17% of the FDI outflows in 2018 (UNCTAD, 2019). This internationalization has undoubtedly had important implications on these countries' exchange rates, which have been strictly controlled by different currency policies until recently. For instance, China fixed its exchange rate in 1995 to the US dollar and maintained that peg until July 2005, while the ruble has been trading freely since 2014, when Russia abandoned a previous peg. Moreover, the exchange rate system in India has

[1] In 2001, the term BRIC was coined for Brazil, Russia, India, and China. South Africa joined this group of countries in 2010, leading to BRICS.

transited from a fixed exchange rate regime to the present form of freely determined exchange rate regime since 1993, while Brazil and South Africa adopted a floating exchange rate regime in 1999 and 2000, respectively. Although there are some attempts to analyze the impact of GPR on stock returns and volatility in emerging countries (Balcilar et al., 2016; Ferreira et al., 2018; Ramiah and Graham, 2013; Redl, 2018; Hoque and Zaidi, 2020), they do not study the impact on exchange rate volatility.

The second contribution relates to the consideration of both in-sample and out-of-sample forecasts. Most studies dealing with forecasting exchange rate volatility are limited to in-sample predictability (see Poon and Granger, 2013, for a review), although in-sample predictability does not guarantee out-of sample forecasting gains (Rapach and Zhou, 2013). Furthermore, although exchange rate volatility has been found to increase with economic policy uncertainty (Krol, 2014; Balcilar et al., 2016; Christou et al., 2018), up to our knowledge, there is no attempt in the literature to predict exchange rate volatility in BRICS countries using GPR. Against this backdrop, we consider both global and domestic (country-specific) geopolitical risks variables, and for robustness analysis, we also consider the predictive capability of oil price uncertainty for exchange rate volatility. Finally, we replicate the forecasts for the UK exchange rate volatility.

Third, this paper uses a GARCH-MIDAS-X model (Engle et al., 2013) in order to accommodate available data frequencies, such as daily exchange rate data with monthly GPR data. This model has been proven to be useful to analyse the link between financial and macroeconomic variables (Conrad and Loch, 2015; 2019). Recent applications of this methodology can be found in Liu et al. (2019), Salisu and Gupta (2020) and Salisu et al. (2020).

The main results suggest that the BRICS exchange rates are less vulnerable to GPR when we consider long rage historical data than when recent (short range) data are used. In fact, for the long rage data, we find a negative impact of GPR on exchange rate volatility (except in Russia) and a positive one when we use recent data, suggesting that exchange rate movements are larger in periods of floating rates. China seems to be the least vulnerable country, while the Russian rouble is the most vulnerable currency in our sample. Finally, the BRICS exchange rates are more vulnerable to global than domestic (country-specific) geopolitical risks, a result which evidences the great internationalization and connectedness among international financial markets.

The remainder of the paper is structured as follows. Section 2 describes the methodology. Section 3 presents the data and Section 4 shows the main empirical results. Finally, Section 5 contains some concluding comments and policy implications.

2. Data Description and Preliminary Analyses

The data employed in this study comprise daily exchange rate returns of BRICS countries and the United Kingdom, different measures (historical/long range data, recent and country-specific) of geopolitical risks (GPR, Threat and Attack) as well as oil uncertainty, with the latter used as a proxy for geopolitical risk as well (Demirer et al., 2018), given that historically, wild fluctuations in oil price has been associated with geopolitical events and disaster risks (Hamilton, 2013; Baumeister and Kilian, 2016). Note oil price uncertainty is based on the conditional volatility derived from a GARCH(1,1) model as suggested by Sadorsky (2006). The dollar-based nominal daily exchange rate and the monthly nominal West Texas Intermediate (WTI) oil price data are derived from the Global Financial Data.[2] The exchange rate returns for the considered countries, the geopolitical risks and the oil uncertainty have different start dates, with the earliest period being 1st January, 1862 (for South Africa)[3] while a uniform end date - 31st August, 2020, is adopted for all the variables across the countries of interest.

Besides the oil uncertainty capturing the geopolitical risks, we use a historical data on overall global geopolitical risk of Caldara and Iacoviello (2019),[4] obtained by counting the occurrence of words related to geopolitical tensions, derived from automated texts searches of 3 newspapers (The New York Times, The Chicago Tribune, and The Washington Post) over the monthly period of January, 1899 to August, 2020, as well as the metric based on a wider database of 11 newspapers (The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post) from January, 1985 to August, 2020.

The search associated with global geopolitical risks identifies articles containing references to six groups of words: Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S.

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[2] https://globalfinancialdata.com/.

[3] Data for Brazil, Russia, India, China and the United Kingdom starts on 2nd March, 1920; 28th January, 1992; 2nd March, 1920; 1st April, 1974, and 3rd January, 1900 respectively.

[4] The data is available for download from: https://www.matteoiacoviello.com//gpr.htm.

involvement. Group 2 includes words directly related to nuclear tensions. Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively. Finally, Groups 5 and 6 aim at capturing press coverage of actual adverse geopolitical events (as opposed to just risks), which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war. To arrive at the country-level index for the BRICS (besides Turkey, Mexico, Korea, Indonesia, Saudi Arabia, Argentina, Colombia, Venezuela, Thailand, Ukraine, Israel, Malaysia, and Philippines), Caldara et al., (2019) includes in their search the name of the specific country and words from the above six groups. This data too ranges from January, 1985 to August, 2020. Understandably, groups 1–4 capture threats from geopolitical risks, while groups 5 and 6 encompass the actual acts of geopolitical risks. Note that, following Balcilar et al., (2017), when we use the country-specific geopolitical risks measures, we rely on the differential between the risks of a specific country in the BRICS group to that of the global values of the same, since exchange rates are relative prices.

While the exchange rate returns, the predicted variable in this study, are available in daily (higher) frequency, the predictor variables - geopolitical risk measures, exist in monthly (lower) frequency. This informed the adoption of the GARCH-MIDAS model framework, which is developed using the mixed data sampling technique and allows for the predictability of high frequency series using information from lower frequency series[5]. We hereafter discuss the data features (in terms of the location, spread and shape) with some preliminary analyses (the ARCH and serial correlation tests at specified lags) presented in Table 1, which contains five well labelled panels. The first two panels summarize the historical/long range and recent global measures of the geopolitical risk, the third panel focuses on the country-specific geopolitical risks; the fourth panels summarizes the exchange rate returns the BRICS country and the UK, while the fifth panel global oil uncertainty.

On average, global geopolitical risk measures appear to be lower in recent times compared to the historical/long range period. This is especially observed with respect to GPR and GPR attack, with the duo being more widely spread out from their mean value, an indication of higher volatility in the historical/long range period than in recent time period (see the first and second

[5] Another variant – ADL-MIDAS predicts a lower frequency series using a higher frequency predictor is also well documented in the literature, along with its advantages over uniformed based model frameworks (see Salisu and Ogbonna, 2019; among others).

panels in Table 1). As far as the country-specific GPR is concerned (see third panel in Table 1), the average is in the range of -1.201 and 0.649, with Russia and India corresponding to the least and the highest. Indian GPR appears to be more volatile compared to other BRICS countries, while China's is the least volatile. The exchange rate returns of the BRICS countries and the UK ranged between -0.005 and 0.127, with the UK having not just the least returns on exchange rate, but also a negative return on the average. Russia's exchange rate is found to be the most volatile among the exchange rates considered. Except for Russia GPR and UK exchange rate returns, all the variables in the study are positively skewed, while all the variables are leptokurtic. There is evidence of ARCH effect, level and higher order autocorrelations in all the variables except the exchange rate returns of India, China and the UK. Consequently, the most appropriate model would be one that takes cognizance of the inherent conditional heteroscedasticity and autocorrelations, as well as the mixed data feature of the variables considered.

Table 1: Summary Statistics and Preliminary Analysis

	Mean	*Std. Dev.*	*Skewness*	*Kurtosis*	*N*	*ARCH(5)*	*ARCH(10)*	*ARCH(20)*	*Q(5)*	*Q(10)*	*Q(20)*	*Q^2(5)*	*Q^2(10)*	*Q^2(20)*
Historical Geo-Political Risk Data [January 1899 – August 2020] – Monthly Frequency														
GPR	86.395	69.989	2.27	10.66	1460	12.827^{a}	7.380^{a}	3.822^{a}	55.257^{a}	70.405^{a}	120.660^{a}	67.761^{a}	81.630^{a}	84.626^{a}
Threat	66.323	53.144	2.36	13.10	1460	42.252^{a}	22.657^{a}	11.704^{a}	70.674^{a}	84.579^{a}	155.840^{a}	209.340^{a}	259.920^{a}	268.010^{a}
Attack	151.376	241.681	4.09	23.38	1460	4.919^{a}	4.275^{a}	2.122^{a}	67.721^{a}	94.213^{a}	140.940^{a}	27.767^{a}	49.782^{a}	51.363^{a}
Recent Geo-Political Risk Data [January 1985 – August 2020] – Monthly Frequency														
GPR	85.923	63.717	2.99	16.39	428	10.982^{a}	5.727^{a}	4.533^{a}	21.004^{a}	23.057^{a}	53.559^{a}	56.701^{a}	58.084^{a}	89.502^{a}
Threat	88.029	70.203	3.03	16.79	428	10.667^{a}	5.755^{a}	4.084^{a}	24.945^{a}	27.331^{a}	55.971^{a}	59.312^{a}	63.997^{a}	86.899^{a}
Attack	75.394	64.444	4.11	26.28	428	2.254^{b}	1.349	2.920^{a}	4.299^{a}	20.381^{a}	47.064^{a}	11.353^{b}	13.476	22.535
Country Specific Geo-Political Risk [January 1985 – August 2020] – Monthly Frequency														
Brazil	-0.408	0.948	0.45	3.39	428	2.134^{c}	1.992^{b}	1.615^{b}	14.987^{a}	33.569^{a}	54.575^{a}	12.016^{b}	19.960^{b}	32.510^{b}
Russia	-1.201	0.968	-0.18	3.18	427	1.484	1.185	0.830	23.512^{a}	45.624^{a}	75.386^{a}	7.849	11.701	34.082^{b}
India	0.649	1.067	0.50	3.48	427	2.578^{b}	2.980^{a}	2.050^{a}	18.202^{a}	34.322^{a}	59.585^{a}	11.291^{b}	28.424^{a}	41.546^{a}
China	0.154	0.551	0.73	3.62	428	5.871^{a}	4.186^{a}	2.455^{a}	11.236^{a}	39.082^{a}	65.056^{a}	27.255^{a}	49.631^{a}	56.412^{a}
South Africa	0.152	0.642	0.48	3.30	428	5.383^{a}	3.868^{a}	2.255^{a}	12.344^{a}	41.320^{a}	66.315^{a}	24.917^{a}	45.188^{a}	50.512^{a}
Exchange Rate Returns – Daily Frequency														
Brazil	0.127	1.193	22.43	1327.82	28321	0.111	0.061	0.033	216.630^{a}	661.860^{a}	1481.300^{a}	0.558	0.617	0.664
Russia	0.086	7.696	0.39	3492.89	7535	194.767^{a}	97.307^{a}	48.524^{a}	763.320^{a}	766.370^{a}	770.780^{a}	997.550^{a}	997.550^{a}	997.550^{a}
India	0.012	0.541	32.93	2525.65	28246	0.104	0.053	0.027	9.143	15.230	32.030	0.520	0.536	0.547
China	0.011	0.521	51.00	3578.69	11689	0.001	0.001	0.001	0.534	1.848	4.330	0.003	0.006	0.012
South Africa	0.008	0.634	6.82	391.90	46235	64.833^{a}	33.600^{a}	18.419^{a}	68.950^{a}	118.640^{a}	178.410^{a}	357.960^{a}	386.660^{a}	448.600^{a}
UK	-0.005	1.072	-127.61	20574.02	34279	0.000	0.000	0.000	3.891	5.632	8.577	0.000	0.001	0.001
Oil Uncertainty [October 1859 – August 2020] – Monthly Frequency														
Oil uncertainty	92.190	190.109	6.17	54.50	1931	33.796^{a}	48.095^{a}	44.619^{a}	63.671^{a}	188.260^{a}	230.730^{a}	215.030^{a}	574.970^{a}	621.810^{a}

Note: The presence of conditional heteroscedasticity and serial autocorrelation are tested using the ARCH test and the Ljung Box Q- and Q^2- statistics, respectively, with significance indicating presence. Statistical significance of the estimates at 1%, 5% and 10%, are respectively denoted by “a”, “b” and “c”.

3. Methodology

The relationship between geopolitical risk and exchange rate volatility is rooted in the concept of systematic risk, where the risk affects the overall market rather than a particular asset, and it is both unpredictable and unavoidable (see Fontinelle, 2019). The geopolitical risk can be described as a form of systematic risk since it also impacts the overall market. In terms of the direction of relationship, and according to the literature, it will depend on each country's exposition to GPR, on whether GPR are country-specific or global, on each country's macroeconomic fundamentals, on the safe haven properties of its currency and on the exchange rate regime in each of the countries. Thus, currencies that are perceived risky will experience higher volatilities with a rise in geopolitical risk (GPR).

To test the research hypothesis, we employ the GARCH-MIDAS framework whose choice is motivated by the available data for the variables of interest. As previously noted, the predicted series which is related to exchange rate is available in daily (higher) frequency while the predictor series - geopolitical risk measures, exist in monthly (lower) frequency. Using data at their seemingly natural frequencies helps to circumvent the problem of information loss resulting from data aggregation or dis-aggregation in order to have uniform frequency. The GARCH-MIDAS model essentially has four equations as specified below with the constant conditional mean equation and the conditional variance equation which is further multiplicatively decomposed into high and low frequency components (see Engle et al., 2013 for technical details):

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \qquad \forall \; i = 1,\ldots,N_t \tag{1}$$

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

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k\left(\omega_1,\omega_2\right) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k\left(\omega_1,\omega_2\right) = \frac{\left[k/(K+1)\right]^{\omega_1-1} \times \left[1-k/(K+1)\right]^{\omega_2-1}}{\sum_{j=1}^{K}\left[j/(K+1)\right]^{\omega_1-1} \times \left[1-j/(K+1)\right]^{\omega_2-1}} \tag{4}$$

$$\varepsilon_{i,t} \left| \Phi_{i-1,t} \sim N(0,1) \right. \tag{5}$$

where $r_{i,t} = ln\left(S_{i,t}\right) - ln\left(S_{i-1,t}\right)$ denotes the return series for exchange rates; $S_{i,t}$ is the cost of domestic currency to 1 US dollar; on the i^{th} day of month t; N_t represents the number of days in month t; μ denotes the unconditional mean of the exchange rates returns; $h_{i,t}$ and τ_i indicate the short- and long -run components of the conditional variance part of equation (1) which are further expanded in equations (2) and (3). The former - $h_{i,t}$ (the short run component) assumes a GARCH(1,1) process where α and β in equation (2) are the ARCH and GARCH terms respectively and we expect that $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The latter - τ_i which is the long-term component, originally varying monthly, is structured to daily frequency as given in equation 3 where m is the long-run constant, θ is slope coefficient (the sum of weighted rolling window exogenous variable) that indicates impact of GPR on the long run return volatility of exchange rate, $\phi_k\left(\omega_1, \omega_2\right)$ is the beta polynomial weighing scheme, with $\phi_k\left(\omega_1, \omega_2\right) \geq 0,\ k = 1, \ldots, K$ and summing up to unity for model identification, X_{i-k} denotes the predictor variable (GPR), while the superscripted "rw" indicates that the rolling window framework Is employed; and the random shock $\varepsilon_{i,t}$ conditional on $\Phi_{i-1,t}$ that indicates the information set that is available at $i-1$ day of month t, is normally distributed.

In addition to testing the impact of GPR on the return volatility of exchange rate of the BRICS (which essentially involves in-sample predictability, we also evaluate the out-of-sample forecast performance of the GARCH-MIDAS-based predictive model since in-sample predictability may not necessarily translate into improved out-of-sample forecasts (see Campbell, 2008; Rapach and Zhou, 2013).. Here, the relative RMSE is used [i.e. $RMSE_u / RMSE_r$ where $RMSE_u$ is for the unrestricted (GPR-based) model while $RMSE_r$ is for the restricted (benchmark) model][6] and two variants of the GARCH-MIDAS framework are comparatively evaluated: the one that accounts for the GPR predictor (which can be technically described as GARCH-MIDAS-X) and the other variant which excludes the predictor series. Consequently, the relative RMSE value that is less than one is considered to indicate support for the GPR-based model over the benchmark,

[6] The results of alternative forecast measures such as the Mean Absolute Error and the Mean Percentage Forecast Error with similar conclusions as those obtained using the RMSE are available upon request.

while value above one implies otherwise. We utilize 50:50 data split for the in-sample and out-of-sample forecast evaluation respectively while the 75:25 data split is also used for robustness. Multiple out-of-sample (30 days and 60 days ahead) forecast horizons are evaluated while the rolling window method is used to obtain the forecasts.

4. Results and Discussion

We present here the GARCH-MIDAS based estimation result of the nexus between exchange rate volatility of the BRICS countries and the different measures of geopolitical risks. The results are threefold. First, we analyse the predictability of the exchange rate volatility of BRICS countries, using the different proxies of global geopolitical risks (such as historical/long range, recent, and structural GPRs) and country-specific geopolitical risks. Second, we examine the relative forecast performance of the GARCH-MIDAS-X models (where "X" denotes the predictor series) with the conventional GARCH-MIDAS that ignores the GPR predictor. Third, we consider a relatively large open economy using the UK economy as a case study. The idea is to see whether a larger open economy will behave differently from the emerging (BRICS) economies. Additionally, we consider another source of systematic risk due to oil price uncertainty to further examine the vulnerability of the BRICS exchange rates to global risks. We take each in turn.

4.1 Do geopolitical risks possess predictive capability for exchange rate volatility?

In attempting to answer the question on the predictive capability of geopolitical risks for exchange rate volatility of BRICS countries, we present the GARCH-MIDAS-X model parameter estimates in Table 2. As earlier stated, the different GARCH-MIDAS-X models are distinguished by the proxy of geopolitical risk employed. Consequently, Table 2 comprises three panels - the first relating to global historical GPR, the second to GPR threats, and the third to GPR attacks -. The model parameters include the unconditional mean for exchange rate returns (μ); ARCH coefficient (α); GARCH coefficient (β); the slope coefficient (θ) that denotes the stance of predictability, or otherwise; adjusted beta polynomial weight (w); as well as the long run constant term (m). Across the three constructs of global historical geopolitical risks, the sum of the ARCH and GARCH coefficients is less than unity in all cases, which is an indication that the impact of shocks on the exchange rate volatility of the BRICS countries would only be transient, might just persist over a long time period. In other words, there is evidence of high but mean reverting volatility persistence, and this is consistent across the GPR proxies considered. Across the geopolitical risk proxies, all the estimates of the adjusted beta weight are greater than one and statistically significant. This is indicative of the weighting scheme assigning higher weights to the immediate past observations than those that are far apart. The impact of the geopolitical risk on exchange rate volatility of the BRICS is determined by the statistical significance of the slope coefficient (θ). In other words, we test the null hypothesis that the slope coefficient is not statistically different form zero, such that a rejection of the null hypothesis at any of the standard critical regions would imply significance, and imperatively, predictability. The slope coefficients (θ) in our estimated GARCH-MIDAS models, using separately global historical/long range GPR, GPR threats and GPR attacks, are found to be negative and statistically significant for all the BRICS countries except for Russia that showed significantly positive coefficients. This result is consistent across the global historical geopolitical risk proxies adopted. Imperatively, while the exchange rate volatility of all the BRICS countries except Russia reduces as geopolitical risks heighten, the reverse is the for the Russian exchange rate volatility. The latter may be perceived to be riskier than other BRICS countries.

Here, we examine the forecast performance of our GARCH-MIDAS model comprising three different global historical geopolitical risk proxies, using the conventional RMSE statistics. The performance of the GARCH-MIDAS-X model is considered in relative terms with respect to the conventional GARCH-MIDAS model, following the established predictability stance in the previous section. The result on the forecast evaluation is presented in Table 3. As consistent with the RMSE statistic, when comparing two models, the model with the least RMSE value is considered the most preferred and data supported. Consequently, in relative terms (ratio of the RMSE of the GARCH-MIDAS-X to GARCH-MIDAS), values less than one are indicative of an outperformance of the former over the latter. Given that there are three different global historical geopolitical risk proxies (GPR, GPR threats and GPR attacks), this translates to three contending GARCH-MIDAS-X model specifications, differing only with respect to the choice of GPR proxy. Herein, we consider the in-sample period as well as 30- and 60-day out-of-sample periods, across the BRICS countries. We consider also, for the purpose of forecast evaluation, only 50% of the full data sample, and as a form of robustness, 75% of the full data sample (see result in the Appendix).

Table 2: Predictability of exchange rate volatility using recent geopolitical risk [Full Data]

Country	μ	α	β	θ	w	m
			Geopolitical Risk [Historical/Long range Data]			
Brazil	0.0738[a]	0.1004[a]	0.8213[a]	-1.5007[a]	4.9642[a]	3.3303[a]
	[0.0034]	[0.0005]	[0.0004]	[0.0073]	[0.0111]	[0.0159]
Russia	-0.5943[a]	0.0673[a]	0.9327[a]	0.0999[a]	4.9990[a]	-0.0381[b]
	[0.0047]	[0.0012]	[0.0014]	[0.0368]	[1.7230]	[0.0149]
India	0.0000	0.1875[a]	0.7972[a]	-1.8378[a]	3.7969[a]	3.9544[a]
	[0.0030]	[0.0022]	[0.0024]	[0.0001]	[0.0060]	[0.0005]
China	0.0048	0.5041[a]	0.3891[a]	-1.1961[a]	3.4298[a]	2.6506[a]
	[0.0031]	[0.0436]	[0.0247]	[0.3620]	[0.0307]	[0.7987]
South	-0.0001	0.1364[a]	0.8578[a]	-1.1841[a]	4.7691[a]	3.7405[a]
Africa	[0.0004]	[0.0007]	[0.0007]	[0.1137]	[0.0196]	[0.3597]
			Geopolitical Risk Threat [Historical/Long range Data]			
Brazil	0.1124[a]	0.0897[a]	0.8287[a]	-1.2337[a]	4.9652[a]	2.8981[a]
	[0.0042]	[0.0006]	[0.0005]	[0.0074]	[0.0093]	[0.0174]
Russia	-0.6508[a]	0.0671[a]	0.9329[a]	0.0892[b]	4.9971[a]	-0.0285[b]
	[0.0058]	[0.0013]	[0.0015]	[0.0389]	[1.7891]	[0.0135]
India	0.0059	0.1253[a]	0.7305[a]	-0.2368[a]	3.9015[a]	0.5417[a]
	[0.0040]	[0.0021]	[0.0032]	[0.0024]	[0.0614]	[0.0047]
China	0.0021	0.7628[a]	0.0000	-0.9644[a]	2.3717[a]	1.9838[a]
	[0.0044]	[0.0059]	[0.0005]	[0.0238]	[0.0085]	[0.0495]
South	-0.0020[c]	0.2154[a]	0.7802[a]	-4.6392[a]	1.0010[a]	8.3356[a]
Africa	[0.0012]	[0.0022]	[0.0019]	[1.2634]	[0.0194]	[2.2676]
			Geopolitical Risk Attack [Historical/Long range Data]			
Brazil	0.0592[a]	0.1089[a]	0.8271[a]	-0.4629[a]	5.0060[a]	3.0946[a]
	[0.0034]	[0.0008]	[0.0005]	[0.0045]	[0.0107]	[0.0304]
Russia	-0.4276[a]	0.0670[a]	0.9330[a]	0.2960[a]	4.9991[a]	-0.1305[a]
	[0.0017]	[0.0009]	[0.0008]	[0.0822]	[0.7812]	[0.0365]
India	0.0003	0.1940[a]	0.7912[a]	-0.5193[a]	1.0015[a]	3.2203[a]
	[0.0009]	[0.0033]	[0.0030]	[0.0649]	[0.0013]	[0.4026]
China	0.0127	0.0000	0.0027	-0.1492[a]	1.6875[a]	0.4006[a]
	[0.0118]	[0.0003]	[9.80E+05]	[0.0025]	[0.0475]	[0.0023]
South	-0.0006	0.2481[a]	0.7284[a]	-0.1285[a]	2.1839[a]	1.5596[a]
Africa	[0.0006]	[0.0015]	[0.0017]	[0.0074]	[0.0179]	[0.0902]

Note: μ is the unconditional mean for exchange rate returns; α is the ARCH coefficient; β is the GARCH coefficient; θ is the slope coefficient that denotes the stance of predictability of monthly geopolitical risk proxy for daily exchange rate volatility; w **is** adjusted beta polynomial weight; and m is the long run constant term. Figures in square brackets are the standard error of the estimates, while the "a", "b" and "c" indicate statistical significance at 1%, 5% and 10%, respectively.

Table 3: Relative RMSE Results using Historical GPR (50% Data Sample)

Country	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack
	In-Sample			*30-Days Out-of Sample*			*60-Days Out-of Sample*		
Brazil	6.2E-01	1.5E-04	5.4E-01	7.8E-01	4.0E-07	1.8E-02	1.0E+00	1.3E-05	6.2E-02
Russia	9.1E-01	9.0E-01	9.3E-01	9.9E-01	9.6E-01	1.0E+00	1.5E+00	1.4E+00	1.2E+00
India	1.3E-03	2.8E-01	1.3E-03	9.3E-01	1.0E+00	1.1E+00	9.2E-01	1.0E+00	1.1E+00
China	5.8E-03	5.8E-03	5.0E-03	8.3E-04	5.0E-04	2.2E-03	9.5E-04	2.6E-03	6.7E-03
South Africa	4.0E-04	4.2E-04	4.4E-04	8.6E-01	8.5E-01	8.4E-01	8.5E-01	8.4E-01	8.4E-01

A comparison of the forecast performance of the different GARCH-MIDAS-X model constructs (comprising different GPR proxies) with the conventional GARCH-MIDAS model is presented in Table 3, for each of the BRICS countries. In the in-sample period, the GARCH-MIDAS-X model with the different historical/long-range GPR proxies, as single predictor, yielded lower forecast errors than the conventional GARCH-MIDAS model, across all the BRICS countries. The stance of out-performance of the GARCH-MIDAS-X model transcends the in-sample period. Models incorporating separately each of the three historical GPR proxies are found to yield more precise out-of-sample (both 30- and 60-days ahead) forecasts than models that ignore same. This is observed in the cases of China and South Africa. In the case of Brazil, GARCH-MIDAS-X is preferred in all except in the 60-days ahead out-of-sample period when GPR was used as the lone predictor. The historical GPR proxies in the cases of Russia and India are somewhat different as the conventional GARCH-MIDAS are mostly preferred. From the foregoing, the GARCH-MIDAS-X model that incorporates any of the historical GPR proxies is mostly preferred over the conventional GARCH-MIDAS model. This is in addition to the confirmed predictability stance presented in Table 2, showing the relevance of incorporating a measure of geopolitical risks when predicting exchange rate volatility. While the out-performance of the GARCH-MIDAS-X is consistent in the in-sample across the BRICS countries and GPR proxies, the appropriateness of any of the GPR proxies in a predictive model for exchange rate volatility may be dependent on the BRICS country being considered for out-of-sample forecasts.

4.2 Additional Analyses

4.2.1 Are the results sensitive to data samples?

We consider here shorter (more recent) data samples to ascertain whether the predictability stance is sensitive to data samples particularly when compared with the historical data samples. The results are presented in three panels as shown in Table 4. All the relevant parameter estimates required to determine the behavior of long run and short run volatility of exchange rates are found to be statistically significant. The stance of high but mean reverting return volatility persistence is evident based on the sum of ARCH and GARCH terms. The beta weights are all greater than unity, an indication of higher weight assignment to immediate past than far apart time lags. On the predictability of the GPR proxies (θ), although found to be statistically significant regardless of the GPR proxy employed, the estimated coefficients are positive in all cases except China when GPR threat is used and India and China when GPR attack is used. This is quite different from the stance when a longer range of data sample is used, especially with respect to all the BRICS countries except Russia (positively signed both in the long- and short-range data sample) and China (negatively signed both in the long- and short-range data sample). This result shows that the direction of predictability may be sensitive to the chosen data sample, especially with respect to Brazil, India and South Africa. More recent GPR data tend to suggest that exchange rates of Brazil, India and South Africa have become risky in recent times while Russia is all time risky, China seems to be least vulnerable.

The forecast evaluation of the GARCH-MIDAS-X predictive model for the exchange rate volatility of each of the BRICS countries using recent GPR proxies, relative to the conventional GARCH-MIDAS model, is presented in Table 5. In the in-sample period, the GARCH-MIDAS-X models with each of the three GPR proxies as predictor yielded lower forecast errors than the conventional GARCH-MIDAS, especially, in the case of Brazil (GPR and GPR threats only), Russia and South Africa as these showed relative RMSE values less than unity. There were cases of similitude in performance of the GARCH-MIDAS-X and the conventional GARCH-MIDAS models in the case of India in the in-sample period. In the case of China, the conventional GARCH-MIDAS is preferred in the in-sample, regardless of the GPR proxy considered. The GARCH-MIDAS-X models maintain the out-performance in the out-of-sample period, having a larger proportion of relative RMSE less than one, and in other cases, equal to one, which indicates equality between the GARCH-MIDAS-X and the conventional GARCH-MIDAS model. The latter are preferred in the cases of Russia and India, for larger out-of-sample forecast horizon. Generally, the out-performance of the GARCH-MIDAS-X model transcends both short (30-day) and long (60-day) forecast periods. Again, the relevance of the incorporating geopolitical risk as a predictor for BRICS country exchange rate volatility using the MIDAS framework is brought to bear, as it increases the forecast precision over the conventional GARCH-MIDAS model.

Table 4: Predictability of exchange rate volatility using recent geopolitical risk data

Country	μ	α	β	θ	w	m
			Geopolitical Risk [Recent]			
Brazil	0.0366[a]	0.1984[a]	0.7907[a]	7.4181[a]	5.6193[a]	-2.3209[a]
	[0.0046]	[0.0055]	[0.0045]	[1.4147]	[0.2103]	[0.4394]
Russia	-0.1665[a]	0.0671[a]	0.9329[a]	0.2200[a]	4.9999[a]	-0.0628[a]
	[0.0012]	[0.0006]	[0.0006]	[0.0405]	[1.0520]	[0.0125]
India	0.0031	0.1207[a]	0.8779[a]	0.9646[a]	1.9781[a]	0.7468[a]
	[0.0028]	[0.0016]	[0.0014]	[0.3589]	[0.2720]	[0.2813]
China	-0.0004	0.1331[a]	0.7883[a]	-0.6995[a]	1.4064[a]	1.2473[a]
	[0.0023]	[0.0124]	[0.0105]	[0.0586]	[0.0007]	[0.1044]
South Africa	0.0188[a]	0.1181[a]	0.8719[a]	2.6412[a]	3.0768[a]	-0.6556[a]
	[0.0058]	[0.0043]	[0.0038]	[0.4760]	[0.5409]	[0.1285]
			Geopolitical Risk Threat [Recent]			
Brazil	0.0373[a]	0.1940[a]	0.7945[a]	6.8082[a]	4.8898[a]	-2.0175[a]
	[0.0043]	[0.0054]	[0.0044]	[1.1632]	[0.1667]	[0.3444]
Russia	-0.1511[a]	0.0672[a]	0.9328[a]	0.2183[a]	4.9996[a]	-0.0585[a]
	[0.0010]	[0.0005]	[0.0005]	[0.0376]	[0.7210]	[0.0104]
India	0.0034	0.1220[a]	0.8767[a]	1.1957[a]	2.0804[a]	0.5969[a]
	[0.0028]	[0.0017]	[0.0015]	[0.4437]	[0.2183]	[0.2259]
China	-0.0006	0.7872[a]	0.0000	-0.8862[b]	2.2013[a]	1.9813[b]
	[0.0033]	[0.0998]	[0.0006]	[0.4164]	[0.0150]	[0.9301]
South Africa	0.0183[a]	0.1186[a]	0.8725[a]	2.4484[a]	3.2439[a]	-0.4563[a]
	[0.0058]	[0.0042]	[0.0038]	[0.4940]	[0.6251]	[0.1042]
			Geopolitical Risk Attack [Recent]			
Brazil	0.0383[a]	0.2010[a]	0.7939[a]	16.1790[a]	9.3878[a]	-5.4128[a]
	[0.0055]	[0.0047]	[0.0040]	[6.0595]	[0.0081]	[2.0272]
Russia	-0.1820[a]	0.0649[a]	0.9352[a]	0.3649[a]	5.0063[a]	-0.1277[a]
	[0.0013]	[0.0007]	[0.0007]	[0.0702]	[0.4137]	[0.0247]
India	0.0008	0.1209[a]	0.8778[a]	-1.0891[b]	2.9872[a]	2.3430[a]
	[0.0027]	[0.0019]	[0.0018]	[0.4245]	[0.2315]	[0.8979]
China	0.0001	0.2917[a]	0.5749[a]	-1.0068[a]	1.0668[a]	1.6221[a]
	[0.0028]	[0.0585]	[0.0443]	[0.2809]	[0.0045]	[0.4529]
South Africa	0.0224[a]	0.1020[a]	0.8932[a]	4.4988[a]	1.9771[a]	-1.6221[a]
	[0.0059]	[0.0036]	[0.0033]	[1.2336]	[0.2429]	[0.4906]

Note: μ is the unconditional mean for exchange rate returns; α is the ARCH coefficient; β is the GARCH coefficient; θ is the slope coefficient that denotes the stance of predictability of monthly geopolitical risk proxy for daily exchange rate volatility; w **is** adjusted beta polynomial weight; and m is the long run constant term. Figures in square brackets are the standard error of the estimates, while the "a", "b" and "c" superscripts indicate statistical significance at 1%, 5% and 10%, respectively.

Table 5: Relative RMSE Results using Recent GPR (50% Data Sample)

Country	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack
	In-Sample			30-Days Out-of Sample			60-Days Out-of Sample		
Brazil	9.3E-01	8.9E-01	1.1E+00	9.7E-01	9.7E-01	9.6E-01	1.0E+00	9.7E-01	9.6E-01
Russia	9.1E-01	9.1E-01	9.3E-01	9.9E-01	9.9E-01	1.0E+00	1.2E+00	1.1E+00	1.2E+00
India	1.0E+00	1.0E+00	9.9E-01	5.6E+00	5.3E+00	2.5E+00	2.6E+00	2.5E+00	1.3E+00
China	1.3E+00	1.3E+00	1.2E+00	9.7E-01	1.0E+00	9.7E-01	9.7E-01	1.0E+00	9.7E-01
South Africa	9.9E-01	9.9E-01	9.9E-01	1.0E+00	1.0E+00	9.6E-01	1.0E+00	1.0E+00	9.7E-01

4.2.2 Are country-specific GPRs good predictors of exchange rate volatility?

Having confirmed the predictability of global long- and short- range geopolitical risk proxies for exchange rate volatility in the BRICS countries, we further examine the predictability of country-specific GPR proxies. The intuition is to ascertain whether the BRICS exchange rates are vulnerable to both global and domestic geopolitical risks. We present the results in Table 6. In terms of the predictability parameter, we find that three out of the five considered countries are statistically significant namely Brazil, India and South Africa and sign is consistently negative. Interestingly, the same countries exhibit similar features when recent GPR data are utilized. We however find contrasting evidence between the recent global GPR data and the country-specific GPR data. While for the former the sign is positive, it is however negative for the latter. In other words, the exchange rates of Brazil, India and South Africa tend to be more vulnerable to global than domestic (country-specific) geopolitical risks in recent times. Also, the beta weights are still greater than one and implying the immediate past observations are weighted more than observations at far apart time lags.

Table 6: Predictability of exchange rate volatility using country-specific geopolitical risk data

	μ	α	β	θ	w	m
Brazil	0.0435[a]	0.2027[a]	0.7889[a]	-8.39E+02[a]	2.0080[a]	7.3484[a]
	[0.0058]	[0.0052]	[0.0042]	[2.20E+02]	[0.0519]	[1.9250]
Russia	-5.3224[a]	0.0720[a]	0.9280[a]	-4.4809	5.2178	0.0507
	[0.0674]	[0.0051]	[0.0048]	[1.19E+02]	[7.6250]	[1.3444]
India	0.0031	0.1261[a]	0.8724[a]	-1.65E+02[a]	1.0010[a]	2.1990[a]
	[0.0027]	[0.0015]	[0.0013]	[5.75E+01]	[0.1002]	[0.7674]
China	0.0053	1.0000[a]	0.0000	1.43E+03	3.9035	1.64E+05
	[0.0215]	[0.0181]	[0.0000]	[1.39E+07]	[7.60E+02]	[1.59E+09]
South Africa	0.0185[a]	0.1201[a]	0.8701[a]	-1.74E+02[a]	1.3711[a]	2.3206[a]
	[0.0054]	[0.0043]	[0.0040]	[2.99E+01]	[0.1393]	[0.3862]

Note: μ is the unconditional mean for exchange rate returns; α is the ARCH coefficient; β is the GARCH coefficient; θ is the slope coefficient that denotes the stance of predictability of monthly geopolitical risk proxy for daily exchange rate returns; w **is** adjusted beta polynomial weight; and m is the long run constant term. Figures in square brackets are the standard error of the estimates, while the "a", "b" and "c" indicate statistical significance at 1%, 5% and 10%, respectively.

4.2.3 Is Oil Uncertainty a better predictor of exchange rate volatility?

Here, we consider an entirely different measure of uncertainty -the oil price uncertainty-, as a predictor of the exchange rate volatility of BRICS countries. The results are presented in Table 7, much in the same way as previous uncertainty measures. The results here almost align with those obtained using the historical global GPR proxies. The observed exception is the case of India where a positive and significant slope coefficient is obtained, aligns more with the recent/short range GPR proxies. This exception is not unexpected for India as the country is considered the World's 5th largest consumer of oil in the World and the 9th largest importer, since it imports 70% of its oil. Therefore, its exchange rate is expected to be vulnerable to oil shocks, owing to the need to settle high oil import bills due to oil price uncertainty.

Table 7: Predictability of exchange rate volatility using oil uncertainty

	μ	α	β	θ	w	m
Brazil	0.1088[a]	0.0991[a]	0.8218[a]	-0.9957[a]	1.0010[a]	2.4904[a]
	[0.0036]	[0.0008]	[0.0005]	[0.0105]	[0.0062]	[0.0189]
Russia	-0.9136[a]	0.0729[a]	0.9271[a]	0.0858[b]	5.0165[a]	-0.1297
	[0.0099]	[0.0020]	[0.0027]	[0.0393]	[1.1498]	[0.0899]
India	0.0100	0.0324[a]	0.9676[a]	5.04E+03[a]	1.0077[a]	3.53E+04[a]
	[0.0074]	[0.0005]	[0.0005]	[6.82E+02]	[0.1112]	[4.90E+03]
China	0.0012	0.0000	0.0052	-0.1154[a]	1.0021[a]	0.3854[a]
	[0.0048]	[0.0003]	[1.74E+05]	[0.0002]	[0.0027]	[0.0003]
South Africa	0.0008	0.0492[a]	0.9497[a]	-0.9210[a]	2.6307[a]	4.1658[a]
	[0.0015]	[0.0002]	[0.0001]	[0.1529]	[0.0128]	[0.6814]

Note: μ is the unconditional mean for exchange rate returns; α is the ARCH coefficient; β is the GARCH coefficient; θ is the slope coefficient that denotes the stance of predictability of monthly geopolitical risk proxy for daily exchange rate returns; w **is** adjusted beta polynomial weight; and m is the long run constant term. Figures in square brackets are the standard error of the estimates, while "a", "b" and "c" indicates statistical significance at 1%, 5% and 10%, respectively.

From the foregoing, with respect to the predictability of BRICS countries exchange rate returns, we evaluate the forecast errors of GARCH-MIDAS-X models incorporating, separately, country-specific GPRs and oil uncertainty, in relative comparison with the conventional GARCH-MIDAS model. The forecast evaluation result is presented in Table 8, for the in-sample and out-of-sample (30- and 60-day) forecast horizons. We compare the results in Table 8 with those in Tables 3 and 5, corresponding to the historical and recent data stances of the global GPRs. The GARCH-MIDAS-X model incorporating country-specific GPR out-performs the conventional in all the BRICS country except China in the in-sample period, but consistently performed better than the conventional in all but India. For oil uncertainty, the GARCH-MIDAS-X model is preferred over the conventional GARCH-MIDAS in the in-sample (Brazil, Russia and China) and short and long out-of-sample periods (China and South Africa). The case of the out-of sample performance for Russia showed no marked difference between the GARCH-MIDAS-X and the conventional GARCH-MIDAS model. Overall, the GARCH-MIDAS-X models that incorporate, separately, country-specific GPR and oil uncertainty perform relatively better than the conventional GARCH-MIDAS model that does not incorporate the exogenous predictor.

Table 8: Relative RMSE Results using Country-specific GPR and Oil Uncertainty Data (50% Data Sample)

Country	Country Specific GPR	Oil Uncertainty	Country Specific GPR	Oil Uncertainty	Country Specific GPR	Oil Uncertainty
	In-Sample		***30-Day Out-of-Sample***		***60-Day Out-of-Sample***	
Brazil	9.3E-01	5.9E-01	9.5E-01	7.8E-01	9.5E-01	1.0E+00
Russia	8.9E-01	8.9E-01	1.2E+00	1.0E+00	1.3E+00	1.0E+00
India	1.0E+00	1.0E+00	2.9E-01	8.1E+00	8.9E-01	9.4E+00
China	2.4E+00	5.7E-03	9.7E-01	8.3E-04	9.7E-01	9.5E-04
South Africa	9.9E-01	2.2E+00	9.4E-01	9.2E-01	9.7E-01	9.3E-01

4.2.4. Are GPRs proxies and Oil Uncertainty good predictors of UK exchange rate volatility?

Here, we consider the predictability of the UK exchange rate volatility following the same measures as the BRICS case. The predictability result from the GARCH-MIDAS-X estimation is presented in Table 9, while the forecast evaluation result is presented in Table 10. The GARCH-MIDAS-X parameter estimates are not all statistically significant as it regards the UK exchange rate returns. The UK exchange rate returns exhibit permanent volatility persistence as the sum of the ARCH and GARCH terms equals one. Predictability is confirmed for short-range GPR and GPR threat, since the slope coefficients are found to be positive and statistically significant. Like the BRICS, this outcome suggests that the UK exchange rate is also vulnerable to geopolitical tension. In other words, as the pound exchange rate is perceived risky, a rise in GPR may heighten bullish investors' sentiment about the foreign exchange market and by extension raises the level of exchange rate volatility.

On the forecast performance, we find the GARCH-MIDAS-X model out-performing the conventional GARCH-MIDAS model when any of the three historical GPR proxies and oil uncertainty are separately used as predictor of the BRICS countries exchange rate volatility in the in-sample period, while non-distinguishable out-performance was observed when recent GPR proxies are considered as predictors, since the relative RMSE values are approximately equal to one (see result from Table 10). The performance of the GARCH-MIDAS-X model relative to the conventional GARCH-MIDAS again transcends the in-sample period, as similar pattern in both specified out-of-sample periods (30- and 60-days ahead forecast periods). We can convincingly conclude that the different GPR proxies (especially, the historical data) and oil uncertainty are good predictors of UK exchange rate volatility, and their incorporation into the GARCH-MIDAS framework increase the precision over a GARCH-MIDAS framework that does not incorporate these predictors.

Table 9: Predictability of United Kingdom exchange rate volatility

	μ	α	β	θ	w	m
Historical GPR	-0.0427[a]	1.0000[a]	0.0000	1.83E+04	5.1552[a]	2.70E+04
	[0.0109]	[0.0008]	[0.0001]	[4.55E+05]	[0.5977]	[6.71E+05]
Historical GPR	41.3850[a]	0.0300[b]	0.9700[a]	1.94E+04	14.2150	3.16E+04
Threat	[0.2327]	[0.0119]	[0.0118]	[2.08E+05]	[161.5000]	[2.93E+04]
Historical GPR	-0.0059	1.0000[a]	0.0000	-2.88E+03	1.1258[a]	3.31E+04
Attack	[0.0046]	[0.0010]	[0.0001]	[6.94E+04]	[0.0011]	[7.99E+05]
Recent GPR	-0.0046	0.0536[a]	0.9356[a]	0.1073[b]	1.2861	0.2880[a]
	[0.0056]	[0.0023]	[0.0034]	[0.0544]	[1.3206]	[0.0476]
Recent GPR Threat	-0.0046	0.0536[a]	0.9356[a]	0.0967[b]	1.3352	0.2951[a]
	[0.0056]	[0.0023]	[0.0034]	[0.0492]	[1.4340]	[0.0449]
Recent GPR Attack	-0.0045	0.0539[a]	0.9363[a]	0.0098	37.0340	0.3763[a]
	[0.0056]	[0.0023]	[0.0033]	[0.0346]	[192.3300]	[0.0385]
Oil Uncertainty	-0.0474[a]	1.0000[a]	0.0000	1.80E+04	49.5800	5.79E+05
	[0.0124]	[0.0003]	[0.0001]	[2.28E+06]	[70.9310]	[7.33E+04]

Note: μ is the unconditional mean for exchange rate returns; α is the ARCH coefficient; β is the GARCH coefficient; θ is the slope coefficient that denotes the stance of predictability of monthly geopolitical risk proxy for daily exchange rate returns; w **is** adjusted beta polynomial weight; and m is the long run constant term. Figures in square brackets are the standard error of the estimates, while the "a", "b" and "c" indicate statistical significance at 1%, 5% and 10%, respectively.

Table 10: RMSE Results using GPR and Oil Uncertainty for the UK Exchange Rate volatility (50% Data Sample)

Country	**GPR**	**GPR Threat**	**GPR Attack**	**GPR**	**GPR Threat**	**GPR Attack**	**GPR**	**GPR Threat**	**GPR Attack**
	In-Sample			***30-Days Out-of Sample***			***60-Days Out-of Sample***		
Historical GPR	3.8E-04	4.2E-04	4.4E-04	1.3E-01	1.3E-01	1.3E-01	1.5E-01	1.4E-01	1.5E-01
Recent GPR	1.0E+00	1.0E+00	1.0E+00	9.9E-01	9.9E-01	1.0E+00	1.0E+00	1.0E+00	1.0E+00
Oil Uncertainty		9.4E-01			6.0E-00			6.0E-00	

4.2.5 Economic Significance

Drawing from Liu et al. (2019), we further test the economic significance of our predictive model over the conventional GARCH-MIDAS model. The intuition here is to ascertain the economic gains of incorporating the GPR proxies and oil uncertainty in our predictive GARCH-MIDAS model. Essentially, the GARCH-MIDAS model that includes a GPR proxy or oil uncertainty is compared with the GARCH-MIDAS variant with realized volatility. A typical mean-variance utility investor allocates a specific proportions of portfolio to different investment options in contrast to a risk free asset, using an optimal weight, w_t, defined as

$$w_t = \frac{1}{\gamma}\frac{\theta\hat{r}_{t+1} + (\theta - 1)\hat{r}_{t+1}^f}{\theta^2\hat{\sigma}_{t+1}^2} \tag{6}$$

where γ is a coefficient of risk aversion; θ is the leverage ratio; $\hat{r}_{t+1}$ is the exchange rate volatility forecast at time $t+1$; $\hat{r}_{t+1}^f$ is a risk-free asset (say, Treasury bill rate); and $\hat{\sigma}_{t+1}^2$ represents return volatility estimate that is based on a 30-day moving window of daily returns. The corresponding certainty equivalent return for investors' optimal weight, w_t, is defined as

$$CER = \overline{R}_p - 0.5(1/\gamma)\sigma_p^2 \tag{7}$$

where $\overline{R}_p$ and σ_p^2 are the mean and variance, respectively, of the portfolio return in the out-of-sample period; $R_p = w\theta(r - r^f) + (1-w)r^f$ denotes the portfolio returns, with its variance defined as $Var(R_p) = w^2\theta^2\sigma^2$, where σ^2 denotes the excess return volatility. The economic significance determination is obtained by maximizing the objective function of a utility as given in (8) below

$$\begin{aligned} U(R_p) &= E(R_p) - 0.5(1/\gamma)Var(R_p) \\ &= w\theta(r - r^f) + (1-w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \end{aligned} \tag{8}$$

We report four key estimates - returns, volatility, certainty equivalent returns and Sharpe ratio, computed as $SP = (R_p - r^f)/\sqrt{Var(R_p)}$. Evidence of economic gain is confirmed if our predictive model yields the highest returns, CER and SP; and least volatility (Liu et al., 2019). The results are presented in Table 11, considering different levels of risk aversion and leverage ratios. The results show that our predictive model variants (especially the variants incorporating historical and recent GPR-Attack, and oil uncertainty) provide higher economic gains but with higher risks than the conventional GARCH-MIDAS model, when risk aversion level and leverage ratio are assumed to be 1 and 5, respectively. This stance is consistent across the BRICS countries, while the same cannot be said of the UK. Also, with respect to Russia, India and China, our predictive model variants with each of the uncertainty proxies showed evidence of economic gains, having higher returns as well as higher risks. The results is consistent across the different specified risk aversion and leverage ratios, where high returns are associated with high risks. From the foregoing, while the incorporation of uncertainty proxies provides some economic gains with respect to the returns, the associated risk levels are also high. However, judging by the Sharpe ratio, our predictive model appears to yield higher returns amidst the high level of risk in the market. Imperatively, incorporating GPR (historical, recent or country specific) and oil uncertainty in the predictive model for BRICS country exchange rate volatility is both statistically and economically significant.

Table 11: Out-of-sample economic gains with specific risk aversion and leverage ratio.

Model	Brazil				Russia				India				China				South Africa				UK			
	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP
$\gamma=1;\quad \theta=5$																								
Benchmark	1.984	0.333	1.760	0.763	2.399	0.875	2.328	0.914	9.665	6.507	9.617	3.184	40.493	41.362	40.478	6.056	1.697	0.110	1.439	0.462	3.651	3.525	3.542	1.122
GPR_H	1.551	0.072	1.323	0.025	**10.144**	**7.367**	**10.080**	**3.169**	**9.976**	**6.591**	**9.926**	**3.284**	**43.980**	**43.936**	**43.966**	**6.402**	1.556	0.032	1.302	0.069	3.543	3.369	3.435	1.089
THREAT_H	1.564	0.084	1.337	0.069	**10.173**	**7.368**	**10.108**	**3.179**	**10.088**	**6.747**	**10.039**	**3.289**	**43.996**	**44.099**	**43.983**	**6.393**	1.555	0.031	1.301	0.063	3.537	3.356	3.428	1.088
ATTACK_H	**2.244**	**0.509**	**2.025**	**0.982**	**10.099**	**7.284**	**10.035**	**3.170**	**9.798**	**6.497**	**9.749**	**3.238**	**46.848**	**45.354**	**46.834**	**6.727**	**1.737**	**0.138**	**1.480**	**0.519**	3.636	3.513	3.527	1.116
GPR_R	1.548	0.071	1.320	0.014	**9.355**	**6.674**	**9.292**	**3.024**	**9.986**	**6.588**	**9.936**	**3.289**	**43.924**	**44.267**	**43.911**	**6.370**	1.536	0.020	1.282	-0.054	3.519	3.329	3.410	1.082
THREAT_R	1.501	0.043	1.273	-0.208	**9.327**	**6.648**	**9.263**	**3.019**	**10.003**	**6.609**	**9.953**	**3.290**	**44.012**	**44.678**	**43.998**	**6.354**	1.532	0.018	1.278	-0.086	3.510	3.315	3.401	1.080
ATTACK_R	**2.002**	**0.357**	**1.781**	**0.766**	**11.590**	**8.707**	**11.524**	**3.404**	**9.824**	**6.530**	**9.775**	**3.240**	**45.962**	**45.523**	**45.948**	**6.583**	**1.726**	**0.131**	**1.470**	**0.503**	3.637	3.512	3.528	1.117
GPR_CS	1.754	0.200	1.532	0.470	**11.860**	**8.920**	**11.793**	**3.454**	**10.064**	**6.721**	**10.015**	**3.286**	**44.956**	**45.924**	**44.943**	**6.406**	1.544	0.023	1.289	0.004				
Oil Uncertainty	**2.065**	**0.385**	**1.842**	**0.840**	**10.974**	**8.131**	**10.909**	**3.307**	**9.873**	**6.485**	**9.823**	**3.271**	**44.082**	**42.512**	**44.069**	**6.524**	**1.734**	**0.135**	**1.477**	**0.518**	3.625	3.472	3.515	1.117
$\gamma=1;\quad \theta=8$																								
Benchmark	2.288	0.514	2.063	1.038	1.830	0.424	1.759	0.440	11.950	8.360	11.902	3.599	49.611	51.089	49.596	6.725	1.872	0.215	1.614	0.707	4.543	4.963	4.434	1.346
GPR_H	1.709	0.165	1.481	0.405	**12.204**	**9.114**	**12.139**	**3.531**	**12.263**	**8.403**	**12.213**	**3.698**	**53.837**	**54.166**	**53.823**	**7.105**	1.666	0.097	1.411	0.391	4.416	4.785	4.307	1.313
THREAT_H	1.731	0.184	1.504	0.436	**12.231**	**9.108**	**12.166**	**3.541**	**12.399**	**8.596**	**12.349**	**3.702**	**53.867**	**54.379**	**53.854**	**7.095**	1.664	0.095	1.410	0.389	4.408	4.769	4.299	1.312
ATTACK_H	**2.617**	**0.734**	**2.398**	**1.252**	**12.157**	**9.019**	**12.093**	**3.534**	**12.075**	**8.311**	**12.026**	**3.653**	**56.870**	**55.412**	**56.857**	**7.432**	**1.931**	**0.254**	**1.675**	**0.768**	4.526	4.953	4.416	1.340
GPR_R	1.705	0.165	1.478	0.398	**11.338**	**8.349**	**11.274**	**3.390**	**12.273**	**8.397**	**12.224**	**3.703**	**53.801**	**54.611**	**53.788**	**7.071**	1.630	0.076	1.376	0.313	4.386	4.738	4.278	1.306
THREAT_R	1.630	0.119	1.402	0.250	**11.307**	**8.321**	**11.243**	**3.384**	**12.286**	**8.417**	**12.236**	**3.703**	**53.918**	**55.126**	**53.905**	**7.054**	1.622	0.071	1.368	0.294	4.375	4.721	4.267	1.303
ATTACK_R	**2.317**	**0.548**	**2.097**	**1.045**	**13.771**	**10.590**	**13.705**	**3.757**	**12.105**	**8.352**	**12.056**	**3.655**	**55.925**	**55.765**	**55.911**	**7.282**	**1.917**	**0.245**	**1.661**	**0.753**	4.526	4.952	4.417	1.340
GPR_CS	1.995	0.348	1.773	0.765	**14.055**	**10.807**	**13.989**	**3.806**	**12.377**	**8.568**	**12.328**	**3.701**	**54.980**	**56.556**	**54.967**	**7.106**	1.643	0.081	1.388	0.347				
Oil Uncertainty	**2.389**	**0.580**	**2.166**	**1.110**	**13.110**	**9.958**	**13.045**	**3.665**	**12.154**	**8.284**	**12.104**	**3.686**	**53.820**	**52.264**	**53.806**	**7.231**	**1.926**	**0.250**	**1.668**	**0.764**	4.510	4.897	4.401	1.340
$\gamma=2;\quad \theta=5$																								
Benchmark	1.764	0.083	1.652	0.763	1.971	0.219	1.936	0.914	5.605	1.627	5.581	3.184	21.018	10.341	21.011	6.056	1.620	0.027	1.491	0.462	2.597	0.881	2.543	1.122
GPR_H	1.547	0.018	1.433	0.025	**5.844**	**1.842**	**5.812**	**3.169**	**5.760**	**1.648**	**5.735**	**3.284**	**22.762**	**10.984**	**22.755**	**6.402**	1.550	0.008	1.423	0.069	2.544	0.842	2.489	1.089
THREAT_H	1.554	0.021	1.440	0.069	**5.858**	**1.842**	**5.826**	**3.179**	**5.816**	**1.687**	**5.791**	**3.289**	**22.770**	**11.025**	**22.763**	**6.393**	1.549	0.008	1.422	0.063	2.541	0.839	2.486	1.088
ATTACK_H	**1.894**	**0.127**	**1.784**	**0.982**	**5.821**	**1.821**	**5.789**	**3.170**	**5.671**	**1.624**	**5.646**	**3.238**	**24.196**	**11.338**	**24.189**	**6.727**	**1.640**	**0.034**	**1.512**	**0.519**	2.590	0.878	2.535	1.116
GPR_R	1.546	0.018	1.432	0.014	**5.450**	**1.668**	**5.418**	**3.024**	**5.765**	**1.647**	**5.740**	**3.289**	**22.734**	**11.067**	**22.727**	**6.370**	1.540	0.005	1.413	-0.054	2.531	0.832	2.477	1.082
THREAT_R	1.522	0.011	1.408	-0.208	**5.435**	**1.662**	**5.404**	**3.019**	**5.773**	**1.652**	**5.749**	**3.290**	**22.778**	**11.169**	**22.771**	**6.354**	1.538	0.004	1.411	-0.086	2.527	0.829	2.472	1.080
ATTACK_R	**1.773**	**0.089**	**1.663**	**0.766**	**6.567**	**2.177**	**6.534**	**3.404**	**5.684**	**1.632**	**5.659**	**3.240**	**23.753**	**11.381**	**23.746**	**6.583**	**1.635**	**0.033**	**1.507**	**0.503**	2.590	0.878	2.536	1.117
GPR_CS	1.649	0.050	1.538	0.470	**6.702**	**2.230**	**6.668**	**3.454**	**5.804**	**1.680**	**5.779**	**3.286**	**23.250**	**11.481**	**23.243**	**6.406**	1.544	0.006	1.417	0.004				
Oil Uncertainty	**1.804**	**0.096**	**1.693**	**0.840**	**6.259**	**2.033**	**6.226**	**3.307**	**5.708**	**1.621**	**5.684**	**3.271**	**22.813**	**10.628**	**22.806**	**6.524**	**1.639**	**0.034**	**1.510**	**0.518**	2.584	0.868	2.530	1.117
$\gamma=2;\quad \theta=8$																								
Benchmark	1.916	0.128	1.804	1.038	1.687	0.106	1.652	0.440	6.747	2.090	6.723	3.599	25.577	12.772	25.570	6.725	1.708	0.054	1.579	0.707	3.044	1.241	2.989	1.346
GPR_H	1.626	0.041	1.512	0.405	**6.874**	**2.279**	**6.842**	**3.531**	**6.903**	**2.101**	**6.879**	**3.698**	**27.690**	**13.542**	**27.684**	**7.105**	1.605	0.024	1.478	0.391	2.980	1.196	2.925	1.313
THREAT_H	1.637	0.046	1.524	0.436	**6.887**	**2.277**	**6.855**	**3.541**	**6.971**	**2.149**	**6.947**	**3.702**	**27.705**	**13.595**	**27.699**	**7.095**	1.604	0.024	1.477	0.389	2.976	1.192	2.921	1.312
ATTACK_H	**2.080**	**0.184**	**1.971**	**1.252**	**6.850**	**2.255**	**6.818**	**3.534**	**6.809**	**2.078**	**6.785**	**3.653**	**29.207**	**13.853**	**29.200**	**7.432**	**1.737**	**0.064**	**1.609**	**0.768**	3.035	1.238	2.980	1.340
GPR_R	1.625	0.041	1.511	0.398	**6.441**	**2.087**	**6.409**	**3.390**	**6.909**	**2.099**	**6.884**	**3.703**	**27.673**	**13.653**	**27.666**	**7.071**	1.587	0.019	1.460	0.313	2.965	1.185	2.911	1.306
THREAT_R	1.587	0.030	1.473	0.250	**6.425**	**2.080**	**6.393**	**3.384**	**6.915**	**2.104**	**6.890**	**3.703**	**27.731**	**13.782**	**27.724**	**7.054**	1.583	0.018	1.456	0.294	2.960	1.180	2.905	1.303
ATTACK_R	**1.931**	**0.137**	**1.820**	**1.045**	**7.657**	**2.648**	**7.624**	**3.757**	**6.825**	**2.088**	**6.800**	**3.655**	**28.734**	**13.941**	**28.727**	**7.282**	**1.730**	**0.061**	**1.602**	**0.753**	3.035	1.238	2.980	1.340
GPR_CS	1.769	0.087	1.658	0.765	**7.800**	**2.702**	**7.766**	**3.806**	**6.960**	**2.142**	**6.936**	**3.701**	**28.262**	**14.139**	**28.255**	**7.106**	1.593	0.020	1.466	0.347				
Oil Uncertainty	**1.966**	**0.145**	**1.855**	**1.110**	**7.327**	**2.489**	**7.294**	**3.665**	**6.849**	**2.071**	**6.824**	**3.686**	**27.682**	**13.066**	**27.675**	**7.231**	**1.735**	**0.063**	**1.606**	**0.764**	3.027	1.224	2.972	1.340

Note: Bold figures indicate cases where our predictive model yielded higher returns than the benchmark GARCH-MIDAS model

5. Conclusion

In this paper, we examine the vulnerability of the BRICS exchange rates to geopolitical risks (GPR) using alternative measures ranging from global (historical and recent) GPR data to country-specific GRP data. Consequently, we set out to achieve two objectives: first, to test the predictability of GPR for exchange rate volatility; second, to further evaluate the out-of-sample predictability of GPR based using multiple forecast horizons, both 50:50 and 75:25 data splits and rolling window method to obtain the forecasts. We construct a GARCH-MIDAS-X model in order to accommodate available data frequencies for relevant series and by extension circumvent information loss and any associated bias. Using the long range data, we find that, on average, the BRICS exchange rates are less vulnerable to geopolitical risks, however, recent (short range) data suggest otherwise. We also find contrasting evidence between the recent global GPR data and the country-specific GPR data implying that the BRICS exchange rates are more vulnerable to global than domestic (country-specific) geopolitical risks in recent times while China seems to be the least vulnerable. The GARCH-MIDAS model that accounts for the GPR data outperforms the benchmark (the conventional GARCH-MIDAS model without the GPR predictor) both for the in-sample and out-of-sample forecasts. When the analysis is replicated for a more developed (open) economy, the conclusion about the vulnerability of exchange rates to geopolitical risks in recent times is upheld. The incorporation of GPR proxies are also relevant economically in the prediction of BRICS countries exchange rate volatility.

An extension of this study that examines the hedging options for foreign exchange markets of the BRICS against geopolitical risk will further enrich the literature. These are areas we set aside for future research.

References

Abadie, A., Gardeazabal, J., 2008. Terrorism and the world economy. European Economic Review 52, 1-27.

Aganin, A., Peresetsky, A. 2018. Volatility of ruble exchange rate: Oil and sanctions. Applied Econometrics, 52, 5-21.

Antonakakis, N., Gupta, R., Kollias, C., Papadamou, S., 2017. Geopolitical risks and the oil-stock nexus over 1899-2016. Finance Research Letters 23(C), 165-173.

Aysan, A.F., Demir, E., Gozgor, G., Lau, C.K., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. Research in international business and finance 47, 511-518.

Balcilar, M., Gupta, R., Segnon, M., 2016. The role of economic polity uncertainty in predicting US recessions: A mixed-frequency Markov-switching vector autoregressive approach. Economics: The Open-Access, Open-Assessment E-Journal 10, 1-20.

Balcilar, M., Gupta, R., Pierdzioch, C., Wohar, M.E., 2017. Do terror attacks affect the dollar-pound exchange rate? A nonparametric causality-in-quantiles analysis. The North American Journal of Economics and Finance 41, 44-56.

Balcilar, M., Bonato, M., Demirer, R., Gupta, R., 2018. Geopolitical risks and stock market dynamics of the BRICS. Economic Systems 42(2), 295-306.

Bank of International Settlements, 2019. Triennial Central Bank Survey, September 2019.

Barunik, J., Krehlik, T., Vacha, L., 2016. Modeling and forecasting exchange rate volatility in time-frequency domain. European Journal of Operational Research 251, 329-340.

Baumeister, C.J., Kilian, L., 2016. Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us. Journal of Economic Perspectives 30(1), 139-160.

Benavides, G., Capistrán, C., 2012. Forecasting exchange rate volatility: the superior performance of conditional combinations of time series and option implied forecasts. Journal of Empirical Finance 19(5), 627-639.

Berkman, H., Jacobsen, B., Lee, J.B., 2011. Time-varying rare disaster risk and stock returns. Journal of Financial Economics 101(2), 313-332.

Bloomberg, S., Hess, G.D., Orphanides, A., 2004. The macroeconomic consequences of terrorism. Journal of Monetary Economics 51(5), 1007-1032.

Brounen, D., Derwall, J., 2010. The impact of terrorist attacks on international stock markets. European Financial Management 16(4), 585-598.

Caldara, D., Iacoviello, M., 2019. Measuring geopolitical risk. Working paper, Board of Governors of the Federal Reserve Board, 1222.

Caldara, D., Iacoviello, M., Markiewitz, A., 2019. Country-specific geopolitical risk. Board of Governors of the Federal Reserve Board, Mimeo.

Campbell, J.Y., 2008. Viewpoint: estimating the equity premium, Canadian Journal of Economics, 41, 1–21.

Caporale, G.M, Ali, F.M., Spagnolo, N., 2015. Exchange rate uncertainty and international portfolio flows: a multivariate GARCH-in-Mean Approach. Journal of International Money and Finance 54, 70-92.

Caporale, G.M, Ali, F.M., Spagnolo, F., Spagnolo, N., 2017. International portfolio flows and exchange rate volatility in emerging Asian countries. Journal of International Money and Finance 76(C), 1-15.

Chen, A.H., Siems, T.F., 2004. The effects of terrorism on global capital markets. European Journal of Political Economy 20, 349-366.

Cheng, C.H., Chiu, C.W., 2018. How important are global geopolitical risks to emerging countries? International Economics 156, 305-325.
Chesney, M., Reshetar, G., Karaman, M., 2011. The impact of terrorism on financial markets: an empirical study. Journal of Banking and Finance 35(2), 253-267.
Christoffersen, P., Diebold, F.X., 2006. Financial asset returns, direction of change forecasting and volatility dynamics. Management Science 52(8), 1273-1287.
Christou, C., Gupta, R., Hassapis, C., Suleman, T., 2018. The role of economic uncertainty in forecasting exchange rate returns and realized volatility: evidence from quantile predictive regressions. Journal of Forecasting 37(7), 705-719.
Conrad, C., Loch, K., 2015. Anticipating long-term stock market volatility. Journal of Applied Econometrics 30, 1090-1114.
Conrad, C., Loch, K., 2019. Two are better than one: volatility forecasting using multiplicative component GARCH-MIDAS models. Journal of Applied Econometrics 35(1), 19-45.
Demirer, R., Gupta, R., Suleman, M.T., Wohar, M.E., 2018. Time-varying rare disaster risks, oil returns and volatility. Energy Economics, 75(C), 239–248.
Diebold, F.X., Nerlove, M., 1989. The dynamics of exchange rate volatility: A multivariate latent factor ARCH model. Journal of Applied Econometrics 4, 1-21.
Eckstein, Z., Tsiddon, D., 2004. Macroeconomic consequences of terror: theory and the case of Israel. Journal of Monetary Economics 51, 971-1002.
Engle, R.F., Ghysels, E., Sohn, B., 2013. Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics 95, 776-797.
Eun, C., Resnick, B., 1988. Exchange rate uncertainty, forward contracts and international portfolio selection. Journal of Finance 43, 197-215.
Ferreira, T.S., Xavier, G.C., Martins, O.S., 2018. Political uncertainty and risk premium in the Brazilian stock market. Journal of Financial innovation, early view, 62.
Fatum, R., Yamamoto, Y., 2016. Intra-safe haven currency behavior during the global financial crisis. Journal of International Money and Finance 66(C), 49-64.
Fidora, M., Fratzscher, M., Thimann, C., 2007. Home bias in global bond and equity markets: the role of real exchange rate volatility. Journal of International Money and Finance 26(4), 631-655.
Fontinelle, Amy. (Sep 30, 2019). Systematic Risk. Received from https://www.investopedia.com/terms/s/systematicrisk.asp#:~:text=Systematic%20risk%20refers%20to%20the,a%20particular%20stock%20or%20industry.
Gkillas, K., Gupta, R., Wohar, M.E., 2018. Volatility jumps: The role of geopolitical risks. Finance Research Letters 27, 247-258.
Gkillas, K., Gupta, R., Pierdzioch, C., 2020. Forecasting realized gold volatility: is there a role of geopolitical risks? Finance Research Letters 35, 101280.
Glick, R., Taylor, A.M., 2010. Collateral damage: trade disruption and the economic impact of war. Review of Economics and Statistics 92(1), 102-127.
Gupta, R., Gozgor, G., Kaya, H., Demir, E., 2019. Effects of geopolitical risks on trade flows: evidence from the gravity model. Eurasian Economic Review 9, 515-530.
Hamilton, J.D., 2013. Historical Oil Shocks. In Routledge Handbook of Major Events in Economic History, edited by Randall E. Parker and Robert Whaples, 239-265, New York: Routledge Taylor and Francis Group.
Hansen, P.R, Lunde, A., 2005. A forecast comparison of volatility models: does anything beat a GARCH(1,1)? Journal of Applied Economics 20(7), 873-889.

Hoque, M.E., Zaidi, M.A., 2020. Global and country-specific geopolitical risk uncertainty and stock return of fragile emerging economies. Borsa Istanbul Review 20, 197-213.
Huang, T., Wu, F., Yu, J., Zhang, B., 2015. International political risk and government bond pricing. Journal of Banking and Finance 55, 393-405.
Jeanne, O., Rose, A.K., 2002. Nose trading and exchange rate regimes. Quarterly Journal of Economics 117(2), 537-569.
Krol, R., 2014. Economic policy uncertainty and exchange rate volatility. International Finance 17(2), 241-256.
Liu, J., Ma, F., Tang Y., Zhang, Y., 2019. Geopolitical risk and oil volatility: A new insight. Energy Economics, 84, 104548.
Narayan, P.K, Narayan, S., Khademalomoom, S., Phan, D.H.B., 2017. Do terrorist attacks impact exchange rate behavior? New international evidence. Economic Inquiry 56(1), 547-561.
Pastor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of Financial Economics 110(3), 520-545.
Poon, S.H., Granger, C.W.J., 2003. Forecasting volatility in financial markets: A review. Journal of Economic Literature 41(2), 478-539.
Ramiah, V., Graham, M., 2013. The impact of domestic and international terrorism on equity markets: Evidence from Indonesia. International Journal of Accounting and Information Management 21(1), 91-107.
Rapach, D., Strauss, J., 2008. Structural breaks and GARCH models of exchange rate volatility. Journal of Applied Econometrics 23(1), 65-90.
Rapach, D., Zhou, G., 2013. Forecasting Stock Returns. Handbook of Economic Forecasting, Volume 2A, Graham Elliott and Allan Timmermann (Eds.) Amsterdam: Elsevier: 328–383.
Redl, C., 2018. Macroeconomic uncertainty in South Africa. South African Journal of Economics 86(3), 361-380.
Sadorsky, P., 2006. Modeling and forecasting petroleum futures volatility. Energy Economics, 28(4), 467–488.
Salisu, A.A., Gupta, R., 2020. How do Housing Returns in Emerging Countries Respond to Oil Shocks? A MIDAS touch. Emerging Markets Trade and Finance, https://doi.org/10.1080/1540496X.2020.1807322
Salisu, A.A., Gupta, R., Bouri, E., Ji, Q., 2020. The role of global economic conditions in forecasting gold market volatility: Evidence from a GARCH- MIDAS approach. Research in International Business and Finance, 54, 101308.
Salisu, A. A., Ogbonna, A. E., 2019. Another look at the energy-growth nexus: New insights from MIDAS regressions. Energy, 174(C), 69–84.
UNCTAD (2019). Special Economic Zones. World Investment Report.
Walkenhorst, P. and Dihel, N., 2002. The Impact of the Terrorist Attacks of 11 September 2001 on International Trading and Transport Activities. Munich Personal RePEc Archive, MPRA 12277.
Yang, K., Wei, Y., Li, S., He, J., 2021. Geopolitical risk and renewable energy stock markets: An insight from multiscale dynamic risk spillover. Journal of Cleaner Production 279, 123429.

Appendix

Table A1: Relative RMSE Results (75% Data Sample)

Country	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack	GPR	GPR Threat	GPR Attack
	In-Sample			30-Days Out-of-Sample			60-Days Out-of-Sample		
Historical GPR Data									
Brazil	1.0E+00	1.0E+00	1.0E+00	6.6E-01	9.0E-01	9.5E-01	6.1E-01	9.0E-01	9.3E-01
Russia	2.2E-02	2.2E-02	2.0E-02	1.0E+00	1.0E+00	9.4E-01	1.0E+00	1.0E+00	9.8E-01
India	4.7E-01	5.2E-01	3.5E-01	2.5E+01	7.8E-01	6.5E-01	2.3E+01	7.1E-01	6.2E-01
China	1.5E+00	2.6E+00	2.4E+00	1.0E+00	9.4E-01	9.4E-01	1.0E+00	9.4E-01	9.3E-01
South Africa	1.0E+00	4.2E+00	1.1E+00	1.0E+00	1.1E+00	1.1E+00	1.0E+00	1.1E+00	1.1E+00
UK	1.1E+00	1.2E+00	1.3E+00	5.1E-02	2.4E-01	5.1E-02	5.4E-02	2.6E-01	5.4E-02
Recent GPR Data									
Brazil	9.9E-01	9.8E-01	1.0E+00	1.0E+00	9.9E-01	1.0E+00	9.9E-01	9.9E-01	9.9E-01
Russia	7.7E-02	7.6E-02	2.0E-02	1.1E+00	1.1E+00	9.5E-01	9.9E-01	9.9E-01	9.8E-01
India	6.9E-01	6.9E-01	6.9E-01	9.5E-01	9.5E-01	9.6E-01	9.6E-01	9.5E-01	9.6E-01
China	9.0E-01	9.9E-01	8.6E-01	1.5E-01	2.1E+00	1.7E-01	1.9E-01	2.1E+00	2.1E-01
South Africa	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00
UK	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00	1.0E+00

Table A2: Relative RMSE Results using Country-specific GPR and Oil Uncertainty Data (75% Data Sample)

Country	Country Specific GPR	Oil Uncertainty	Country Specific GPR	Oil Uncertainty	Country Specific GPR	Oil Uncertainty
	In-Sample		*30-Day Out-of-Sample*		*60-Day Out-of-Sample*	
Brazil	1.0E+00	1.1E+00	9.9E-01	6.0E-01	9.9E-01	5.5E-01
Russia	9.7E-01	2.1E-02	9.9E-01	9.8E-01	1.0E+00	1.0E+00
India	6.9E-01	2.2E+00	9.5E-01	9.6E-01	9.5E-01	9.5E-01
China	1.7E+00	2.5E+00	1.6E-01	9.4E-01	2.0E-01	9.3E-01
South Africa	1.0E+00	1.0E+00	1.0E+00	1.1E-01	1.0E+00	1.1E-01
UK		1.4E+00		5.1E-02		5.4E-02