

Geopolitical Risk and Global Financial Cycle: Some forecasting experiments

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Abstract

In this study, we investigate the connection between geopolitical risk (GPR) and global financial cycle (GFCy) as well as whether the former has predictive value for the out-of-sample predictability of the latter. We utilize both the historical and recent GPR data and their variants namely GPR act covering all ‘acts’ that constitute geopolitical risk such as war, nuclear invasion and terrorism and GPR threat which represents threats of these acts. We construct a predictive model that accommodates the salient features of the predicted and predictor series while the forecast evaluation is conducted for both in-sample and out-of-sample periods. Our findings reveal that a rise in GPR discourages investments in risky assets and by implication worsens GFCy. The impact is more severe after the global financial crisis (gfc), and the GPR threat exerts more adverse effect on GFCy compared to GPR act regardless of whether historical GPR or recent GPR is used. Meanwhile, the predictive model of GFCy that accommodates the GPR data outperforms the benchmark model that ignores it both in the in-sample and out-of-sample estimates albeit with improved forecast performance during the post-gfc period and at a longer forecast horizon. However, the recent GPR data which is broader in scope offers better forecast accuracy than the historical GPR data. Additional analyses involving the vulnerability of global economic conditions (GECON) using the measure developed by Baumeister et al. (2020) reveal similar outcomes as GFCy.

Keywords: Geopolitical risk (GPR); GPR threat; GPR act; Global financial cycle; Predictability; Forecast evaluation

JEL codes: C32, C53, G15, N40

1. Introduction

Geopolitical risks (GPR) have been generalized by business investors, market active players, financial institutions and monetary policy authority as an important determinant of investment decisions and the dynamics in stock exchange market (Caldara and Matteo, 2019). Akin to this claim, a survey carried out on the determinants of the investment decisions of 1000 investors shows that about 75 percent of the total respondents expressed concerns regarding the economic consequences of the various military and diplomatic clashes happening globally, putting geopolitical risk ahead of political and economic uncertainty in terms of investment distortions (see Gallup Survey, 2017). Higher geopolitical risks can heighten perception of disastrous outcomes (destruction of human and physical capital, disruption of supply chains, expropriation risk), make investment in risky projects less attractive and lower consumer confidence (Caldara and Matteo, 2019). Additionally, geopolitical risks are recognized alongside economic and policy uncertainties as the “uncertainty trinity” that could influence the performance of an economy (see Carney, 2016). As a result, many investment firms tend to be conscious of the direction of their

funds especially for the regions that are mostly affected by the uncertainties that arise from the components of the geopolitical risk and this in turn drives the volatility in global risky assets as embedded in the Global Financial Cycle (GFCy). Given this stance of the likelihood effects on the global economy, it is reasonable to evaluate the extent to which geopolitical instability, regionally and globally, affects the global financial cycle.

Against this backdrop, we subject the possible connection between GPR and GFCy to empirical scrutiny. Essentially, we test whether information contained in the GPR can be exploited to improve the out-of-sample forecasts of the GFCy. To the best of our knowledge, this study would be the first to explore the out-of-sample predictive prowess of geopolitical risks for movements in global financial cycle. Unlike the GFCy which covers over 1000 risky assets spreading across Europe, North America, Latin America, Asia-Pacific, and Australia as well as commodity prices excluding precious metals, the few related studies linking GPR to financial markets (see for example, Apergis et al., 2017; Balcilar et al., 2018; Bouras et al., 2019; Hoque and Zaidi, 2020; Hui, 2020) are limited in terms of their coverage of risky assets and the analyses are restricted to in-sample predictability which does not necessarily guarantee forecasting gains (Rapach et al., 2008; Rapach and Zhou 2013). Consequently, we approach this study from the global perspective based on the coverage of the GFCy which is particularly useful for portfolio investors seeking investments beyond their geographical locations and our analyses are rendered both for the in-sample and out-of-sample forecasts. With the consideration of GFCy data, we essentially focus on risky assets which offer higher returns and are as well more vulnerable to risks and therefore, outcomes from the study would offer insightful implications for investors.

We hypothesize a negative relationship between GFCy and GPR since the geopolitical risks have the tendency to adversely affect the global financial cycle due to uncertainties caused by GPR which usually make investments unattractive in affected locations. For instance, during the time of political tensions, instability, terrorists' attacks and wars, there are great concerns from the investment decisions of the investors, which in turn restrict the capital flows globally. To this end, we aim in this paper to assess the dependency of the global financial cycle on geopolitical Risk. We construct a predictive model that accommodates the salient features of the predicted and predictor series while the forecast evaluation is conducted for both in-sample and out-of-sample periods.

The empirical analysis involves the following steps. First, relying on the risk-return hypothesis governed by the Arbitrage Pricing Theory (APT)⁵ following the Westerlund and Narayan (2012, 2015)⁶, we construct a predictive model for GFCy where GPR serves as predictor, that accommodates the salient features of the predicted and predictor series while the forecast evaluation is conducted for both in-sample and out-of-sample periods. Second, we conduct the analyses distinctly for the three variants of geopolitical risks namely the composite GPR and its decomposed components described as GPR act and GPR threat where the former accounts for all ‘acts’ that constitute geopolitical risk such as war, nuclear invasion and terrorism, while the latter represents threats of these acts. Third, we replace the GFCy index with the Global Economic Conditions (GECON) indicator developed by Baumeister et al. (2020) which measures the level of global economic conditions (whose details are provided in Section 4.1) for robustness. Since improvements in GFCy may also imply improvements in GECON, these additional analyses serve as a way of testing the consistency in the GPR measure.

Foreshadowing our results, we find that a rise in GPR depresses investments in risky assets and by implication worsens GFCy. The impact is more severe after the global financial crisis (gfc), and the GPR threat exerts more adverse effect on GFCy compared to GPR act regardless of whether historical GPR or recent GPR is used. Meanwhile, our forecast evaluation results show that the predictive model of GFCy that accommodates the GPR data outperforms the benchmark model that ignores the same both in the in-sample and out-of-sample estimates albeit with improved forecast performance during the post-gfc period and at a longer forecast horizon. However, the recent GPR data which is broader in scope offers better forecast accuracy than the historical GPR data. Additional analyses involving the vulnerability of global economic conditions (GECON) using the measure developed by Baumeister et al. (2020) reveal similar outcomes as GFCy.

The remainder of the paper is structured as follows. Section 2 describes the methodology. Section 3 presents the data and preliminary analyses, Section 4 shows the main empirical results while Section 5 concludes the paper.

⁵ The APT allows for systematic risk such as GPR that cannot be reduced by the diversification of an investment portfolio.

⁶ This methodology is extensively used in the literature to analyze return predictability (see for example, Bannigidadmath and Narayan, (2015), Narayan and Bannigidadmath (2015), Narayan and Gupta (2015), Phan et al., (2015), Devpura et al., (2018), Salisu et al., (2019a, 2019b) among others).

2. Methodology

Here, we formulate an empirical model that examines the impact of geopolitical risk (GPR) on global financial cycle (GFCy). There are already numerous studies analyzing the relationship between GPR and financial assets especially stocks, on the basis of the risk-return hypothesis and other portfolio management theories (see, Chen and Siems, 2004; Brounen and Derwall, 2010; Chesney et al., 2011; Apergis et al., 2017; Balcilar et al., 2018; Narayan et al., 2018; Bouras et al., 2019; Ali et al., 2020; Hoque and Zaidi, 2020; Hui, 2020; Yang et al., 2021). We construct a predictive model that connects high risk events to investment in risky assets. Capital inflow and outflow to risky assets shape the GFCy, we therefore hypothesize that a high GPR may discourage investment in risky assets particularly in the regions prone to such risks and therefore a negative relationship is expected between GPR and GFCy. The GPR index accounts for various risks resulting from armed conflicts, elections, political upheaval, governmental changes, civil strife, war and terrorism. In essence, we expect that as global GPR rises, investors will move capital out of risky assets into less risky assets. We specify our model to control for endogeneity bias (that may result from omitting other predictors of GFCy), conditional heteroscedasticity effect (due to the use of high frequency data) and persistence (which is typical of most financial and economic time series) (see Westerlund and Narayan, 2012, 2015):

$$GFCy_t = \alpha + \beta^{adj} GPR_{t-1} + \gamma(GPR_t - \rho GPR_{t-1}) + Control + \varepsilon_t \quad (1)$$

where $GFCy_t$ is the global financial cycle index; GPR is the global geopolitical risk index using the geopolitical risk (GPR); ε_t is the zero mean idiosyncratic error term; and the coefficient β^{adj} measures the relative impact of geopolitical risk on GFCy and we allow for just one lag given the data frequency (monthly data). The specification is replicated for other variants of GPR namely geopolitical risk act (GPRA) and the geopolitical risk threat (GPRT) which are captured distinctly as GPR. We control for oil price given its strong connection with financial markets (see Narayan and Gupta, 2015; Salisu et al., 2019a, 2019b, among others). Note that the original bivariate specification of equation (1) is given as $GFCy_t = \alpha + \beta GPR_{t-1} + \eta_t$, and to resolve any probable endogeneity bias resulting from the correlation between GPR_t and η_t as well as any potential persistence effect, we follow the approach of Lewellen (2004) and Westerlund and Narayan (2012,

2015). Thus, the parameter β^{adj} is derived as $\beta^{adj} = \beta - \gamma(1 - \rho)$ (where ρ measures the degree of persistence in GPR_t) and is described as the bias adjusted OLS estimator of Lewellen (2004) which corrects for any persistence effect in the predictive model. The additional term $\gamma(GPR_t - \rho GPR_{t-1})$ corrects for any endogeneity bias resulting from the correlation between GPR_t and η_t as well as any inherent unit root problem in the predictor series. Accounting for endogeneity bias here is important since there could be several other risk factors capable of undermining the GFCy which are suppressed in equation (1). Such omissions could introduce endogeneity bias resulting from probable correlations between GPR_t and η_t . Also, since we are using monthly frequency, accounting for conditional heteroscedasticity effect may not be out of place as suggested by Westerlund and Narayan (2012, 2013). This is done by pre-weighting all the data by $1/\hat{\sigma}_\eta$ and estimating the resulting equation with the Ordinary Least Squares (OLS). This modified OLS estimator is described as the Feasible Quasi GLS estimator in Westerlund and Narayan (2012, 2015).

We further test whether the predictive value of GPR can be extended to the out-of-sample forecasts as we consider multiple forecast horizons covering 6, 12 and 24 months. In line with the tradition in time series forecasting, we compare the forecast performance of a GPR-based model with a benchmark model (driftless random walk model) that ignores GPR. We employ the Clark and West (2007) [CW] test to examine if the difference in the regression residuals of the two competing models is statistically significant. A typical test equation for the CW test is given as:

$$\hat{f}_{t+h} = (r_{t+h} - \hat{r}_{1t,t+h})^2 - [(r_{t+h} - \hat{r}_{2t,t+h})^2 - (\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h})^2], \quad (2)$$

where r_t is the actual variable being predicted while the one with ‘^’ denotes its predicted series; h denotes the forecast period; $(r_{t+h} - \hat{r}_{1t,t+h})^2$ and $(r_{t+h} - \hat{r}_{2t,t+h})^2$ are respectively the squared errors for the restricted and the unrestricted models; and $(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h})^2$ is the adjusted squared error incorporated in the CW test to correct for any noise that may characterize the forecasts of larger models. In equation [2], the sample average of \hat{f}_{t+h} can be expressed as $MSE_1 - (MSE_2 - \text{adj.})$

where $MSE_1 = P^{-1} \sum (r_{t+h} - \hat{r}_{1,t,t+h})^2$, $MSE_2 = P^{-1} \sum (r_{t+h} - \hat{r}_{2,t,t+h})^2$, $adj. = P^{-1} \sum (\hat{r}_{1,t,t+h} - \hat{r}_{2,t,t+h})^2$, and P is the number of forecast periods considered in the computation of the averages. In testing for equality of forecast performance between the restricted (the benchmark) model and the unrestricted (GPR-based) model, the generated \hat{f}_{t+h} series is regressed on a constant term only and using the resulting t-statistic for a zero coefficient to determine significance. We reject the hypothesis of a zero coefficient if this statistic is greater than +1.282 (for a one sided 0.10 test) or +1.645 (for a one sided 0.05 test) (see Clark and West, 2007). The rejection of the null hypothesis implies the preference for the uncertainty-based model for stock returns. We also employ single forecast measure, i.e., the Root Mean Square Forecast Error (RMSFE) to complement the Clark & West test results. For robustness and consistency, we replace GFCy with Global Economic Condition (GECON) in our model and replicate all the analysis for the latter, since improvements in GFCy often imply improvement in real economic activities. This is also a way of testing the sensitivity of GPR to alternative measures of economic conditions whether financial or real.

3. Data and Preliminary Analysis

To analyse the impact of Geopolitical Risk (GPR) on Global Financial Cycle (GFCy), we utilize monthly data covering the periods of 1980M01 to 2019M04 whose choice is governed by the start and end dates of GFCy. The GPR dataset is based on the work of Caldara and Iacoviello (2019) and is readily accessible on the website of Matteo Iacoviello - <https://www.matteoiacoviello.com/gpr.htm>. We use both the historical and recent variants of the GPR data in all the analyses rendered in this study. The former is 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) starting from January, 1980 while the latter is 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 and regularly updated. The GPR search covers six groups - 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. 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. We further consider two subsets of the main GPR described as GPR threat and GPR act in order to see which of the two has greater impact on GFCy as well as GECON. The GPR Threat essentially covers Groups 1 to 4 of the main GPR while the GPR Act only includes words belonging to Groups 5 and 6 above (see Caldara and Iacoviello, 2019, for technical details).

On the GFCy index series used in this study, the dataset is derived from the works of Miranda-Agrippino and Rey (2020) and Miranda-Agrippino et al. (2020). The former provides the dataset from 1980M01 to 2012M12 while the latter updates to 2019M04 and equally extends the cross-section of risky assets included in the computation of the index from 858 to 1,004 to reflect a compositional change addressing greater visibility of Eastern (Chinese) markets, in line with the composition of the S&P Global index (<https://us.spindices.com/indices/equity/sp-global-1200>). The GFCy data can be downloaded from the website of Professor Silvia Miranda-Agrippino at: <http://silviamirandaagrippino.com/code-data>. Note that GFCy index is essentially generated as the common global factor extracted from a dynamic factor model (DFM) that involves a comprehensive panel of global risky assets including equity and corporate bond indices that represent Europe, North America, Latin America, Asia-Pacific, and Australia as well as commodity prices excluding precious metals. As the assets covered are risky assets, it may not be out of place therefore to expect a connection between the GFCy and GPR.

Meanwhile, in Table 1, we illustrate the summary statistics for the variables of interest. The table presents the mean and standard deviation of each variable across three periods (full, pre-gfc and post-gfc). We find that, on the average, the GFCy is negative for pre-gfc and positive for post-gfc. The positive value implies a surge in capital inflow after the global financial crisis. This is possible because quite often, after a slowdown in global economy, national governments increase spending through bailout and tax holidays which subsequently motivates increase in investment. Note that the GFCy data only runs from 1980 to 2019 which coincides with the historical period and therefore, we do not present summary statistics for GFCy for the recent period. However, since the GPR data are technically described as historical and recent data, we, thus, present their corresponding statistics. For both historical and recent data, we find that there

have been more incidence of geopolitical risk during post-gfc than the pre-gfc particularly for the composite GPR and GPR threat.

In Table 2, we examine the behaviour of GFCy when GPR level rises or falls below its mean value. It is evident from our result that GFCy deteriorates (improves) when the GPR level rises (falls) above (below) its mean value. This outcome is consistent across the three variants of GPR and regardless of whether the GPR is historical or recent.⁷ Figures 1 and 2 further illustrate the relationship between GFCy and GPR as well as its other variants (GPRA and GPRT). The graphical illustrations reveal the negative relationship between GFCy and GPR in historical and recent periods. High volatility is evident from the graph for both pre-gfc and post gfc periods although it is more pronounced during post-gfc. The most prominent volatility in GFCy in pre-gfc period occurs around the September 11, 2001 attack at the world trade centre of the United States of America. This further reinforces our hypothesis that GPR in fact impacts negatively the GFCy. Meanwhile, the most prominent volatility in the post-gfc period is observed immediately after the crisis (gfc) itself. There are other periods of volatility unevenly distributed across the entire sample periods but they are not as pronounced as the two mentioned above.

Table 1: Summary Statistics for important variables

		Historical			Recent		
		full	pre-gfc	post-gfc	full	pre-gfc	post-gfc
GFCy	Mean	1.22E-16	-0.0232	0.0573	-	-	-
	St. dev.	1.0000	1.0559	0.8472	-	-	-
GPR	Mean	104.2386	100.9492	112.3656	82.8483	76.3535	96.0288
	St. dev	57.4223	62.7034	40.6696	60.9726	65.6989	47.5855
GPRA	Mean	87.9346	94.6914	71.2415	76.1626	82.1911	63.9282
	St. dev.	60.0731	66.8236	33.3987	64.5572	75.5805	28.7515
GPRT	Mean	96.1328	86.0626	121.0121	84.1881	75.3993	102.0241
	St. dev.	59.2379	60.5799	47.5411	66.3970	69.9198	54.6313

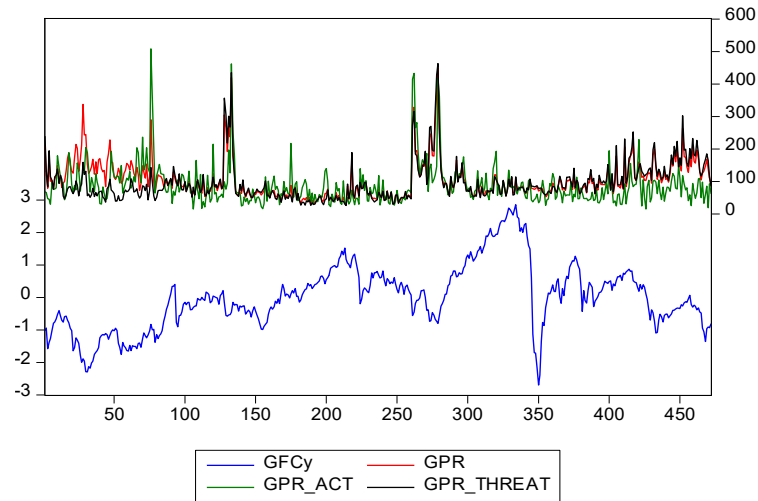
Note: GFCy represents the global financial cycle, GPR is the geopolitical risk, GPRA is geopolitical risk act and GPRT is geopolitical risk threat. Also note that “full” represents the full sample where the entire observations are utilized while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. St. dev. represents standard deviation. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

⁷ Other familiar statistical tests such as serial correlation, conditional heteroscedasticity, endogeneity, persistence and unit root tests are not reported here for brevity but can be made available upon request from the authors.

Table 2: Scenario analysis for global financial cycle (GFCy)

			Historical			Recent		
Historical			full	pre-gfc	post-gfc	full	pre-gfc	post-gfc
GPR	Above	Mean	-0.5039	-0.6503	-0.1564	0.0339	0.1859	-0.1518
		St. dev.	0.9179	1.0335	0.5540	0.8955	1.1214	0.6090
	Below	Mean	0.3106	0.3436	0.1896	0.2632	0.2825	0.1950
		St. dev.	0.9200	0.8838	0.9656	0.9113	0.8492	0.9514
GPRA	Above	Mean	-0.2475	-0.4244	0.0942	0.1210	0.1137	0.0575
		St. dev.	1.0156	1.0110	0.7795	0.9868	1.0044	0.8056
	Below	Mean	0.1526	0.2206	0.0282	0.2236	0.3167	0.0572
		St. dev.	0.9606	1.0092	0.9010	0.8710	0.9000	0.8820
GPRT	Above	Mean	-0.0624	-0.1354	-0.1639	0.0221	0.2896	-0.1803
		St. dev.	0.8324	0.9666	0.5476	0.8533	1.1215	0.6180
	Below	Mean	0.0338	0.0285	0.1943	0.2689	0.2390	0.1912
		St. dev.	1.0799	1.0927	0.9661	0.9289	0.8471	0.9291

Note: GFCy represents the global financial cycle, GPR is the geopolitical risk, GPRA is geopolitical risk act and GPRT is geopolitical risk threat. The “full” represents the full sample where the entire observations are utilized while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. St. dev. represents standard deviation. Also note that “Below” (“Above”) denotes the value of GFCy when global political risk (whether GPR, GPRA, or GPRT) is below (above) its mean. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

**Fig. 1: Historical trends in GFCy and GPRs [GPR, GPRA and GPRT]**

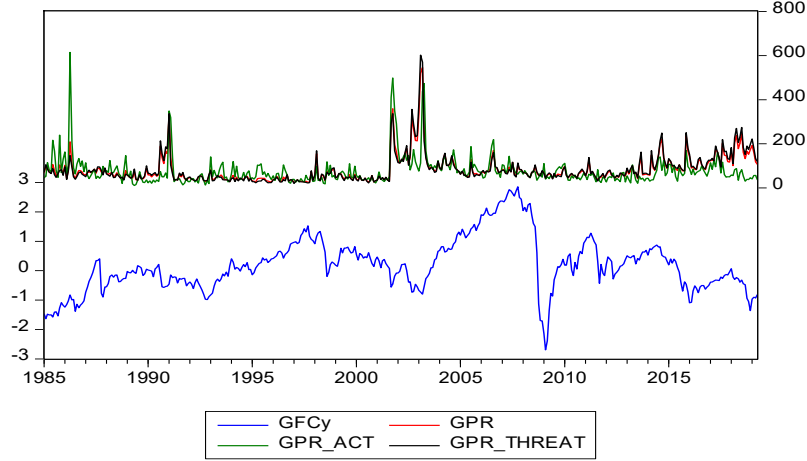


Fig. 2: Recent trends in GFCy and GPRs [GPR, GPRA and GPRT]

4.0 Discussion of Results

4.1 Main Findings

As mentioned in the previous sections, this paper aims to analyze the impact of Geopolitical Risk (GPR) on Global Financial Cycle (GFCy) while also presenting results for Global Economic Conditions (GECON) for robustness purpose. We likewise control for oil, given its connection with financial markets. However, we mainly focus our discussions on the impact of GPR on GFCy and subsequently GECON.⁸ We present our findings on the impact of GPR on GFCy in this section then its impact on GECON under additional results. To test the predictive prowess of our model, we extend our analysis to include forecast evaluations for both in and out-of-sample forecasts for varying forecast horizons. In our analysis, we use two different categories and three variants of GPR: in the first category, we use the historical GPR and the second category, recent GPR. The historical GPR covers a sample period between 1980M01 to 2019M04 while the recent GPR proceeds from 1985M01 to 2019M04. For each category, there are three variants, the GPR, GPRA and GPRT. The GPR represents the overall (aggregated) index for geopolitical risk. On one hand, GPRA is the index for realization of ‘acts’ that constitute geopolitical risk such as war, nuclear invasion and terrorism. While GPRT on the other hand, represents threats of these acts. We do this to isolate the effects of both indexes. We have also partitioned our results into pre-gfc and post-

⁸ See the appendix (Tables A1 and A2) for the entire results involving both GPRs and Oil predictors. The results show a positive connection between oil price return and global financial cycle (see Table A1). This outcome is not surprising as oil price is captured in the GFCy computation and therefore any improvement in the crude oil market (owing to increased level of economic activities) leads to an improvement in GFCy.

gfc periods in order to properly reflect the effect of the global financial crisis on the GPR-GFCy nexus.

In Table 3, we present our predictability results as described above. We find that the global financial cycle is vulnerable to geopolitical risk particularly when the main GPR and GPR threat are considered irrespective of whether the GPR is historical or recent. Apparently, the GPR threat seems to be driving the performance of the main GPR. In other words, the GPR threat exerts more influence on the GFCy than the GPR act. This outcome is also consistent across the three data samples while the adverse effects of GPR threat is more pronounced during the post-gfc period than pre-gfc period. Thus, threats to the acts of geopolitical risks have caused more capital outflow from high-risk regions particularly after the occurrence of the global financial crisis. This result aligns with the studies of Caldara and Iacoviello (2018), Salisu, Lasisi and Tchankam (2022) which also report that threats of geopolitical risks impacted more on the market than actual realization or occurrence of these risks. Similarly, from the analysis of cumulative abnormal returns in the aftermaths of terrorist incidents, Ali et al. (2020) provide strong evidence that the terrorist incidents adversely affect investors' sentiments and confidence in the market as manifested through relatively feeble trading volumes. Recent studies such as Eldor and Melnick (2004), Farooq and Ahmed (2008), Kollias et al. (2010, 2011), Wijeweera (2015), Narayan et al. (2018) and Khan et al. (2020) involving different countries that are prone to some of the components of geopolitical risks such as terrorist attacks, political tension and war, have demonstrated the broad and destructive effects of geopolitical risks on investors' confidence with effects on the performance of stock, forex and money markets.

We also evaluate the forecast power of the predictor (GPR) and therefore we partition the data sample into in-sample and out-of-sample periods using the 75:25 data split respectively. The results of the in-sample and out-of-sample forecast evaluations are presented in Table 4. The forecast evaluations are based on Clark and West (CW, 2007) and root mean square forecast error (RMSFE). The results show that the GPR-based model outperforms - by being positive and significant - the benchmark model (driftless random walk) over the forecast horizons, albeit with improved forecast performance during the post-gfc period and at a longer forecast horizon. However, the recent GPR data which is newer in scope offers better forecast accuracy than the historical GPR data.

Table 3: Predictability results for both Historical and Recent Geopolitical Risk Indices

	Historical GPR			Recent GPR		
	full	pre-gfc	post-gfc	full	pre-gfc	post-gfc
Model 1 (GPR)	-0.0065 ^a (0.0010)	-0.0045 ^a (0.0009)	-0.0083 ^a (0.0045)	-0.0023 ^a (0.0014)	-0.0027 ^b (0.0011)	-0.0068 ^c (0.0040)
Model 2 (GPRA)	-4.40E-05 (0.0014)	-0.0050 ^a (0.0013)	0.0085 ^a (0.0022)	0.0002 (0.0011)	-0.0026 ^c (0.0015)	0.0150 ^a (0.0040)
Model 3 (GPRT)	-0.0062 ^a (0.0014)	-0.0037 ^a (0.0008)	-0.0149 ^a (-4.2768)	-0.0036 ^a (0.0012)	-0.0042 ^a (0.0006)	-0.0088 ^a (0.0033)

Note: ^a, ^b, and ^c represent 1%, 5% and 10% levels of significance respectively. Values in parentheses represent standard errors. Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. However, only the estimates of GPRs are reported for brevity. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. T“full” represents the full sample where the entire observations are utilized while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

Table 4: Clark and West forecast evaluation result

	In Sample Forecasts								
	Full Sample			Pre-GFC			Post-GFC		
	Historical	Recent		Historical	Recent		Historical	Recent	
Model 1	0.7003 ^a [3.3647]	1.6703 ^a [7.3696]		0.0014 [0.0196]	0.1769 ^a [2.3071]		0.6857 ^a [5.6298]	0.8278 ^a [6.5132]	
Model 2	0.0694 ^a [3.0182]	1.6827 ^a [7.3871]		-0.0407 [-0.5609]	0.2148 ^a [2.9821]		1.1361 ^a [6.4238]	1.1127 ^a [6.8303]	
Model 3	0.6561 ^a [2.8777]	1.6642 ^a [7.3365]		-0.1662 ^a [-2.0982]	0.1715 2.2599		0.3295 ^a [2.3933]	0.7351 ^a [5.9998]	
	Out-of-Sample Forecasts: Historical								
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	0.7064 ^a [3.4474]	0.7343 ^a [3.6334]	0.8125 ^a [4.0841]	0.0073 [0.1076]	0.0116 [0.1752]	0.0138 [0.2164]	0.6355 ^a [5.4301]	0.6069 ^a [5.4401]	0.5287 ^a [5.1058]
Model 2	0.6468 ^a [3.1002]	0.6778 ^a [3.2921]	0.7617 ^a [3.7546]	-0.0333 [-0.4698]	-0.0222 [-0.3185]	-0.0202 [-0.3040]	1.0574 ^a [6.2114]	0.9959 ^a [6.1003]	0.8690 ^a [5.7097]
Model 3	0.6640 ^a [2.9587]	0.6954 ^a [3.1412]	0.7824 ^a [3.5910]	-0.1558 ^a [-2.0117]	-0.1464 ^b [-1.9318]	-0.1332 ^b [-1.8323]	0.3094 ^a [2.3629]	0.3156 ^a [2.5401]	0.2967 ^a [2.6248]
	Out-of-Sample Forecasts: Recent								
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	1.7460 ^a [7.7710]	1.7699 ^a [7.9734]	1.7244 ^a [8.0286]	0.1713 ^a [2.2949]	0.1879 ^a [2.5548]	0.1982 ^a [2.8355]	0.7664 ^a [6.2464]	0.7275 ^a [6.1987]	0.6412 ^a [5.8781]
Model 2	1.7619 ^a [7.7960]	1.7876 ^a [8.0022]	1.7424 ^a [8.0602]	0.2046 ^a [2.9156]	0.2185 ^a [3.1414]	0.2114 ^a [3.2014]	1.0386 ^a [6.6161]	0.9671 ^a [6.3795]	0.8482 ^a [6.0001]
Model 3	1.7400 ^a [7.7376]	1.7637 ^a [7.9395]	1.7184 ^a [7.9948]	0.1713 ^a [2.3183]	0.1958 ^a [2.6603]	0.2031 ^a [2.9042]	0.6808 ^a [5.7723]	0.6509 ^a [5.7870]	0.5903 ^a [5.7109]

Note: ^a, ^b, and ^c represent 1%, 5% and 10% levels of significance respectively. Values in square brackets represent t statistics. Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. The full sample covers the entire sampled data while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

Table 5: Root Mean Square Forecast Error

	In Sample Forecasts								
	Full Sample			Pre-GFC			Post-GFC		
	Historical	Recent		Historical	Recent		Historical	Recent	
Model 1	1.6470	1.5041		1.1539	1.1434		1.1590	1.1345	
Model 2	1.6960	1.4682		1.1933	1.0473		0.9120	0.9310	
Model 3	1.7943	1.5149		1.2508	1.1354		1.2904	1.1722	
	Out-of-Sample Forecasts: Historical								
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	1.6576	1.6624	1.6763	1.1406	1.1286	1.1069	1.1407	1.1120	1.0824
Model 2	1.7063	1.7124	1.7275	1.1796	1.1677	1.1450	0.9100	0.8944	0.9014
Model 3	1.8055	1.8107	1.8257	1.2364	1.2234	1.1980	1.2670	1.2473	1.1977
	Out-of-Sample Forecasts: Recent								
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	1.5096	1.5294	1.5899	1.1323	1.1191	1.0936	1.1192	1.0919	1.0608
Model 2	1.4768	1.5008	1.5712	1.0392	1.0376	1.0179	0.9266	0.9255	0.9219
Model 3	1.5201	1.5390	1.5979	1.1226	1.1116	1.0868	1.1538	1.1247	1.0782

Note: Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. The full sample covers the entire sampled data while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

4.2 Additional results

Since improvement in GCFy may imply improvement in real economic activity, *ceteris paribus*, we perform additional analyses where the GFCy is replaced with global economic conditions (GECON) in order to evaluate consistency in the results of GPR as a measure of risk. We show in Figure 3, possible connection between GFCy and GECON as both tend to co-move and therefore, one would expected both to react to a rise in GPR level in a similar fashion, if truly the proposed GPR measure is consistent. Unlike most of the indices used to measure economic

conditions⁹, which only attempt to capture the cyclical component of global real economic activity, and thus restrictive, we consider a more encompassing index of global economic conditions (GECON) developed by Baumeister et al. (2020) which is derived by applying the expectation-maximization algorithm to 16 indicators associated with commodity prices, economic activity, financial indicators, transportation, uncertainty and expectation measures, weather, and energy-related indicators (Baumeister et al., 2020; Salisu et al., 2020a, 2020b). Recent studies by Salisu et al. (2020a, 2020b) which evaluate the comparative performance of the various indices of measuring global economic conditions, find the superior forecast performance of GECON over other indices, on average. Our findings, as illustrated in Table 6 which only reports the results for GPR¹⁰, reveal that the results for GECON are largely similar with those obtained for GFCy. Our CW and RMSFE tests (in Tables 7 and 8 respectively) confirm that the GPR-based model also outperforms the benchmark model for all the periods under consideration.

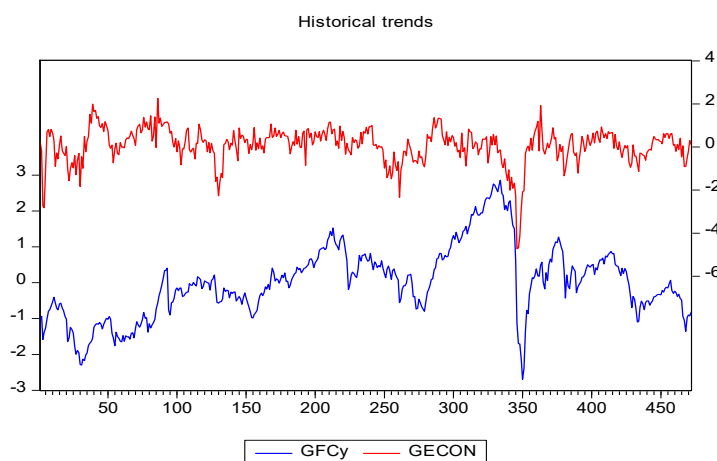


Fig 3: Trends in GFCy and GECON

⁹ These include the world industrial production index (**OECD**) (Baumeister and Hamilton, 2019); **KINDX** which is based on single-voyage dry-cargo freight rates (Kilian, 2009); **RSCF** which is derived from an unbalanced panel of disaggregated data, a cross-section of 61 freight rates for individual shipping routes, for a set of industrial commodities (coal, iron ore, and fertilizer); the **RCPF** which is an extraction of the global factor relating to business cycle fluctuations from the monthly growth rates of real prices of 23 basic industrial and agricultural commodities used as inputs in the production of final goods, excluding precious metals (Alquist et al., 2019); and the **GSPF** which is obtained from monthly global steel production by taking cognisance of the structural break problem of aggregation caused by alterations in the number of reporting countries (see Baumeister et al., 2020; Ravazzolo and Vespignani, 2020)

¹⁰ The results showing the impact of both GPR and Oil on GECON are presented in the appendix (see Table A2). We find that oil has a negative relationship with GECON. This is justifiable since an increase in oil price leads to a rise in the cost of production which consequently impacts negatively on the global economic conditions.

Table 6: Predictability result for Global Economic Conditions (GECON)

Model 1	Historical GRP			Recent GRP		
	Full sample	Pre_GFC	Post_GFC	Full sample	Pre_GFC	Post_GFC
Model 1 (GPR)	-0.0001 ^a (0.0007)	0.0012 ^a (0.0008)	-0.0077 ^a (0.0022)	-0.0030 ^a (0.0010)	-0.0005 (0.0012)	-0.0068 ^a (0.0040)
Model 2 (GPRA)	-0.0006 (0.0006)	-0.0005 (0.0007)	-0.0024 (0.0023)	0.0029 ^a (0.0009)	0.0043 ^a (0.0010)	0.0150 ^c (0.0040)
Model 3 (GPRT)	-0.0041 ^a (0.0008)	-0.0040 ^a (0.0011)	-0.0058 ^a (0.0018)	-0.0036 ^a (0.0009)	-0.0013 ^a (0.0012)	-0.0088 ^a (0.0033)

Note: a, b, and c represent 1%, 5% and 10% levels of significance respectively. Values in parentheses represent standard errors. Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. However, only the estimates of GPRs are reported for brevity. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. The full sample is for the entire observations while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

Table 7: Clark and West forecast evaluation result

In Sample Forecasts									
	Full Sample			Pre-GFC			Post-GFC		
	Historical	Recent		Historical	Recent		Historical	Recent	
Model 1	0.2267 ^a	0.2632 ^a		0.6012 ^a	0.6020 ^a		-0.3837 ^b	-0.2701 ^c	
	[2.2253]	[2.2736]		[5.3164]	[6.0106]		[-1.7577]	[-1.3677]	
Model 2	0.2991 ^a	0.2705 ^a		[0.6956]	0.6442 ^a		0.0326	-0.2098	
	[2.9729]	[2.3927]		6.1197 ^a	[5.8346]		[0.1543]	[-1.0284]	
Model 3	0.3650 ^a	0.2832 ^a		0.7900 ^a	0.6105 ^a		-0.2717 ^c	-0.2645 ^c	
	[3.7216]	[2.4357]		[7.6946]	[5.9943]		[-1.3529]	[-1.3329]	
Out-of-Sample Forecasts: Historical									
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	0.2384 ^a	0.2416 ^a	0.2203 ^a	0.5276 ^a	0.4495 ^a	0.3896 ^a	-0.3714 ^b	-0.3785 ^b	-0.3500 ^b
	[2.3660]	[2.4351]	[2.2803]	[4.6048]	[3.7999]	[3.3910]	[-1.7995]	[-1.9305]	[-1.9669]
Model 2	0.3091 ^a	0.3107 ^a	0.2881 ^a	0.6125 ^a	0.5457 ^a	0.4732 ^a	0.0433	0.0617	0.0946
	[3.1078]	[3.1726]	[3.0211]	[5.2680]	[4.6576]	[4.1268]	[0.2167]	[0.3250]	[0.5462]
Model 3	0.3743 ^a	0.3738 ^a	0.3489 ^a	0.6989 ^a	0.6263 ^a	0.5752 ^a	-0.2626 ^b	-0.2729 ^b	-0.2528 ^b
	[3.8594]	[3.9160]	[3.7500]	[6.5179]	[5.6872]	[5.4008]	[-1.3830]	[-1.5122]	[-1.5435]
Out-of-Sample Forecasts: Recent									
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	0.2665 ^a	0.2381 ^a	0.2246 ^a	0.5601 ^a	0.5394 ^a	0.5782 ^a	-0.2474 ^c	-0.2349 ^c	-0.1942
	[2.3383]	[2.1092]	[2.0485]	[5.6645]	[5.5689]	[6.2097]	[-1.3233]	[-1.3242]	[-1.2028]
Model 2	0.2725 ^a	0.2478 ^a	0.2340 ^a	0.5923 ^a	0.5723 ^a	0.6154 ^a	-0.1918	-0.1547	-0.1135
	[2.4498]	[2.2536]	[2.1941]	[5.4129]	[5.2578]	[5.8880]	[-0.9926]	-0.8391	[-0.6737]
Model 3	0.2864 ^a	0.2567 ^a	0.2424 ^a	0.5730 ^a	0.5607 ^a	0.5981 ^a	-0.2439 ^a	-0.2369 ^b	-0.2065
	[2.5020]	[2.2622]	[2.1988]	[5.7169]	[5.7354]	[6.3677]	[-1.2992]	[-1.3303]	[-1.2768]

Note: ^a, ^b, and ^c represent 1%, 5% and 10% levels of significance respectively. Values in squared brackets represent t statistics. Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. The full sample cover the entire observations are utilized while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

Table 8: Root Mean Square Forecast Error

	In Sample Forecasts								
	Full Sample			Pre-GFC			Post-GFC		
	Historical	Recent		Historical	Recent		Historical	Recent	
Model 1	1.3837	1.3987		1.1983	1.1081		1.6675	1.6623	
Model 2	1.4006	1.4404		1.2585	1.1901		1.6224	1.6579	
Model 3	1.3652	1.3943		1.2069	1.1136		1.6238	1.6551	
Out-of-Sample Forecasts: Historical									
	Full sample			Pre_GFC			Post_GFC		
	15	30	60	15	30	60	15	30	60
Model 1	1.3769	1.3684	1.3633	1.2342	1.2754	1.2949	1.6285	1.6042	1.5387
Model 2	1.3936	1.3849	1.3783	1.2970	1.3294	1.3575	1.5848	1.5450	1.4943
Model 3	1.3582	1.3495	1.3431	1.2528	1.2876	1.2857	1.5850	1.5609	1.4975
Out-of-Sample Forecasts: Recent									
	Full sample			Pre_GFC			Post_GFC)		
	15	30	60	15	30	60	15	30	60
Model 1	1.3936	1.4023	1.4005	1.1165	1.1135	1.0891	1.6207	1.5826	1.5122
Model 2	1.4341	1.4383	1.4305	1.2072	1.2319	1.2052	1.6209	1.6019	1.5504
Model 3	1.3891	1.3988	1.3979	1.1174	1.1082	1.0839	1.6131	1.5764	1.5093

Note: Model 1, Model 2 and Model 3 capture GPR, GPRA and GPRT respectively while Oil price serves as a control in all the models. However, only the estimates of GPRs are reported for brevity. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; and GPRT is the Geopolitical Risk Threat. The full sample cover the entire observations are utilized while “pre-gfc” and “post-gfc” cover the periods before and after the global financial crisis respectively. Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the pre-gfc for both cases have the same end period-12/2007, the start periods vary as previously presented.

5. Conclusion

In this study, we investigate the impact of global geopolitical risk (GPR) on the movement in global financial cycle (GFCy) using both historical and recent GPR datasets as well as their variants involving GPR act and GPR threat where the former accounts for all ‘acts’ that constitute geopolitical risk such as war, nuclear invasion and terrorism, while the latter represents threats of these acts. We formulate an empirical model that allows us to examine the vulnerability of risky assets as captured in the GFCy to geopolitical risk of different variants. Our formulation is based on the hypothesis that investment in risky assets decreases in value during times of high geopolitical risk (GPR). For the purpose of analysis, we adopt the approach of Westerlund and Narayan (2012, 2015) which accommodates the salient features of the predicted and predictor series and the analysis is rendered for both in-sample and out-of-sample periods while sub-samples governed by the global financial crisis are also considered.

Our findings reveal that a rise in GPR discourages investments in risky assets and by implication worsens GFCy. The impact is more severe after the global financial crisis, and the GPR threat exerts more adverse effect on GFCy compared to GPR act regardless of whether historical GPR or recent GPR is used. Meanwhile, our forecast evaluation results show that the predictive model of GFCy that accommodates the GPR data outperforms the benchmark model that ignores it both in the in-sample and out-of-sample estimates albeit with improved forecast performance during the post-gfc period and at a longer forecast horizon. However, the recent GPR data which is broader in scope offers better forecast accuracy than the historical GPR data.

For the purpose of robustness, we replicate all the analyses for global economic conditions (GECON) using the measure developed by Baumeister et al. (2020) and our findings reveal similar outcomes as GFCy, thus, giving some credence to the measures of GPR particularly in terms of the consistency in the response of investment to risks. Since financial markets respond to risks including GPR, these findings offer useful insights into the role of a different form of systematic risk capable of undermining the positive sentiments in the markets and the need to accommodate its behaviour in the valuation of risky assets.

We do hope, subject to data availability, that future studies that examine the out-of-sample predictive prowess of country-specific geopolitical risks for domestic financial markets would be insightful.

Declaration of Conflict of Interest:

The authors do not have any conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement:

The data that support the findings of this study are available on request from the corresponding author. Some of the data are not publicly available due to privacy or ethical restrictions.

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Appendix

Table A1: Predictability results for both Historical and Recent Geopolitical Risk Indices

Model 1	Historical GPR			Recent GPR		
	Full sample	Pre_GFC	Post_GFC	Full sample	Pre_GFC	Post_GFC
GPR	-0.0060 ^a (0.0010)	-0.0045 ^a (0.0009)	-0.0083 ^a (0.0045)	-0.0023 ^a (0.0014)	-0.0027 ^b (0.0011)	-0.0068 ^c (0.0040)
OIL	0.7330 ^a (0.0700)	1.1708 ^a (0.0522)	1.4881 ^a (0.3323)	0.8257 (0.0692)	1.1695 ^a (0.0556)	1.6606 ^a (0.2727)
Model 2						
GPRA	-4.2768 ^c (0.0014)	-0.0050 ^a (0.0013)	0.0085 ^a (0.0022)	0.0002 (0.0011)	-0.0026 ^c (0.0015)	0.0150 ^a (0.0040)
OIL	0.7315 ^a (0.0694)	1.2292 ^a (0.0527)	2.1788 ^a (0.1845)	0.7936 ^a (0.0655)	1.2035 ^a (0.0637)	2.4607 ^a (0.2066)
Model 3						
GPRT	-0.0062 (0.0014)	-0.0037 ^a (0.0008)	-0.0149 ^a (-4.2768)	-0.0036 ^a (0.0012)	-0.0042 ^a (0.0006)	-0.0088 ^a (0.0033)
OIL	0.7363 ^a (0.0717)	1.1514 ^a (0.0523)	0.9758 ^a (3.3866)	0.7386 ^a (0.0743)	1.2098 ^a (0.0534)	1.5212 ^a (0.2546)

Note: ^a, ^b, and ^c represent 1%, 5% and 10% levels of statistical significance respectively. Values in parentheses represent standard errors. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; GPRT is the Geopolitical Risk Threat; OIL represents WTI Oil Price and GFC is Global financial crises; Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the Pre-GFC for both cases have the same end period-12/2007 while the start periods vary as previously presented; Full sample represents a period covering both pre and post GFC.

Table A2: Predictability result for Global Economic Conditions (GECON)

Model 1	Historical GRP			Recent GRP		
	Full sample	Pre_GFC	Post_GFC	Full sample	Pre_GFC	Post_GFC
GPR	-0.0001 ^a (0.0007)	0.0012 ^a (0.0008)	-0.0077 ^a (0.0022)	-0.0030 ^a (0.0010)	-0.0005 (0.0012)	-0.0068 ^a (0.0040)
OIL	-0.2489 ^a (0.0575)	-0.2643 ^a (0.0997)	0.1783 ^a (0.4061)	-0.1633 ^a (0.0561)	-0.3850 ^a (0.1005)	1.6606 ^a (0.2727)
Model 2						
GPRA	-0.0006 (0.0006)	-0.0005 (0.0007)	-0.0024 (0.0023)	0.0029 ^a (0.0009)	0.0043 ^a (0.0010)	0.0150 ^c (0.0040)
OIL	-0.2452 ^a (0.0593)	-0.3574 ^a (0.1028)	1.2787 ^a (0.2398)	-0.1792 ^a (0.0543)	-0.4804 ^a (0.0945)	2.4607 ^a (0.2066)
Model 3						
GPRT	-0.0041 ^a (0.0008)	-0.0040 ^a (0.0011)	-0.0058 ^a (0.0018)	-0.0036 ^a (0.0009)	-0.0013 ^a (0.0012)	-0.0088 ^a (0.0033)
OIL	-0.1710 ^a (0.0563)	-0.3489 ^a (0.0991)	0.3133 (0.1006)	-0.1276 ^b (0.0574)	-0.3709 ^a (0.1021)	1.5212 ^a (0.2546)

Note: ^a, ^b, and ^c represent 1%, 5% and 10% levels of statistical significance respectively. Values in parentheses represent standard errors. GPR is the Geopolitical Risk; GPRA is the Geopolitical Risk Act; GPRT is the Geopolitical Risk Threat; OIL represents WTI Oil Price and GFC is Global financial crises; Historical data ranges from 01/1980 to 04/2018; Recent: 01/1985 to 04/2019; while the Pre-GFC for both cases have the same end period-12/2007 while the start periods vary as previously presented; Full sample represents a period covering both pre and post GFC.