Geopolitical Risks, Returns, and Volatility in Emerging Stock Markets: Evidence from a Panel GARCH Model

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Abstract
In this article, we analyze the role of country-specific and global geopolitical risks (GPRs) on the returns and volatility of 18 emerging market economies over the monthly period of 1998:11 to 2017:06. For our purpose, we use a panel Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach, which offers substantial efficiency gains in estimating the conditional variance and covariance processes by accounting for interdependencies and heterogeneity across economies, unlikein a time series-based GARCH model. We find that, while country-specific GPRs do not have an impact on stock returns, and the positive effect on equity market volatility is statistically weak. But when we consider a broad measure of global GPR, though there is still no significant effect on returns, the impact on volatility is both economically and statistically stronger than that obtained under the country-specific GPRs, thus highlighting the dominance of global rather than domestic shocks.

Keywords: emerging economies, geopolitical risks, panel GARCH, returns and volatility, stock markets

JEL CLASSIFICATION: C33, G15

Financial market returns and its volatility (often associated with uncertainty) are among the most important indicators for practitioners, as its helps them in capital budgeting and portfolio management decisions as they directly reflect companies' financial health and future prospects (Apergis et al. 2017). In addition, for academics, financial market movements based on predictors challenge the idea of market efficiency, and in turn, assists in building realistic asset pricing models (Rapach and Zhou 2013). Hence, determining factors that drives financial market returns and volatility is of paramount importance to both practitioners and academics in finance.Given this, we aim to analyze (for the first time) the role played by country-specific and global geopolitical risks (GPR), in affecting movements of 18 emerging economy stock markets, namely Turkey, Mexico, Korea, Russia, India, Brazil, China, Indonesia, Saudi Arabia, South Africa, Argentina, Colombia, Venezuela, Thailand, Ukraine, Israel, Malaysia, and Philippines.

The news-based GPR indices that measure geopolitical risks used in this article has been recently developed by Caldara and Iacoviello (2017) and Caldara, Iacoviello, and Markiewitz (2017), and includes not only terror attacks, but also other forms of geopolitical tensions like war risks, military threats, Middle East tensions. These indices not only relate to geopolitical events of the global world, but are also available at country-specific levels for the 18 emerging markets we analyze in this article. Hence, this index allows us to capture GPRs of various forms in a continuous fashion, and allows us to go beyond the effect of specific events at a specific point in time, and in turn, provides a more holistic view of GPRs.

We concentrate on GPR, since they are often cited by central bankers, financial press and business investors as one of the determinants of investment decisions, and hence, are believed to affect business cycles and financial markets (Caldara and Iacoviello 2017). When more than 1000 investors were surveyed by Gallup in 2017, 75 percent of respondents expressed concerns about the economic impact ofthe various military and diplomatic conflicts taking place around the world. In the process, geopolitical risk was rankedahead of political and economic uncertainty.[1] In addition, Carney (2016) included geopolitical risk, along with economic and policy uncertainty, among an "uncertainty trinity" that could have significantadverse economic effects. More recently, in the April 2017 EconomicBulletin of the European Central Bank, and in the October 2017 World Economic Outlook of the International Monetary Fund, geopoliticaluncertainties are highlighted as a salient risk to the economic outlook. Now, given that GPRs affect the economic conditions of both developed and emerging markets (Caldara and Iacoviello 2017) and asset prices are functions of the state of the economy (Balcilar et al., 2018a), it is expected, intuitively, that stock market movements are likely to be affected by risks associated with geopolitical events.

For our purpose, we use the panel Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach of Cermeño and Grier (2006), applied to monthly data covering the period of 1998:11 to 2017:06. This approach offers substantial efficiency gains in estimating the conditional variance and covariance processes by accounting for interdependencies and heterogeneity across economies (Lee 2010). A major advantage of using a panel GARCH approach is that we are able to capture possible cross-sectional dependence (CD) whereas a single country, i.e., time-series GARCH model lacks the ability to incorporate such behavior. This is understandably important given the strong interconnectedness among financial markets of emerging economies in a modern day globalized world.

Note that global-level GPR indices have been used recently by Apergis et al. (2017), Caladara and Iacoviello (2017), Balcilar et al., (2018a), and Bouri et al. (2018) to study the impact on returns and/or volatility of country-specific conventional stock markets, global Islamic equity and bond markets and also stocks of leading defense companies primarily in a time-series set-up. However, to the best of our knowledge this is the first attempt to use a panel-GARCH approach to study the role of country-specific and global GPRs on returns and volatility of 18 emerging stock markets. In the process, our article also adds to the related literature of terror attacks in determining movements of financial market returns and volatility (see e.g., Kollias et al. (2010, 2011a, 2011b, 2013a, 2013b), Balcilar et al. (2017, 2018b)), and Gupta et al. (2017), and references cited therein). In sum, researchers (particularly, Kollias et al., (2010, 2011a, 2011b, 2013a)) find that terror attacks on the domestic economy and on major financial markets (as well as global GPRs), though tends to affect both returns (negatively) and volatility (positively), the effect on the latter is more dominant. In this regard, the above results seem to provide support to the evidence obtained by Fernández and Lucey (2008). These authors, while analyzing the causes behind structural breaks in the volatility of stock returns, identify he role of economic, political, and financial events in the emerging markets. In case the break dates matched with such events, it was found to be primarily related to domestic rather than global economic and political scenarios.

The contributions of our article are multiple: (a) As indicated above, we add the the literature on terror attacks and financial market movements, but the GPR indices used by us are much broader, as it includes not only terror attacks but also other forms of geopolitical tensions like war risks, military threats, Middle East tensions, and hence, captures a wider array of exogenous global uncertainty. Moreover, unlike the dummy variables used to capture dates of terror attacks, which could also correspond with another major global event, we are able to capture in a continuous fashion multiple geopolitical risks; (b) We extend the work of Balcilar et al., (2018a), who considered the impact of GPRs on the stock markets of Brazil, Russia, India, China, and South Africa, by not only looking at 13 other emerging markets, but also comparing the importance of country-specific and global GPRs, and (c) Most importantly, given that financial markets in the world economy are interconnected, we pursue a panel data approach that controls for CD, rather than a time series approach in which each countries are treated separately. In the process, our results are likely to be more reliable and robust, as it controls for stock market dependence.

Data Description

Monthly data on geopolitical risk (GPR) are based on the work of Caldara and Iacoviello (2017), and Caldara, Iacoviello, and Markiewitz (2017).[2] Caldara and Iacoviello (2017) constructs the GPR index by counting the occurrence of words related to geopolitical tensions, derived from automated text-searches in leading 11 national and international 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). Then, Caladara and Iacoviello (2017) calculate the index by counting, in each of the above-mentioned 11 newspapers, the number of articles that contain the search terms above for every month starting in 1985. The index is then normalized to average a value of 100 in the 2000–2009 decade, so that a GPR index value of, say 200, indicates that newspaper mentions of rising geopolitical risk in that month were twice as frequent as they were during the 2000s.[3]

The search 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. 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 each of the 18 emerging countries (Turkey, Mexico, Korea, Russia, India, Brazil, China, Indonesia, Saudi Arabia, South Africa, Argentina, Colombia, Venezuela, Thailand, Ukraine, Israel, Malaysia, and Philippines), Caldara, Iacoviello, and Markiewitz (2017) includes in their search the name of the specific country and words from the above six groups. Understandably, groups 1–4 capture threats from geopolitical risks, while groups 5 and 6 encompass the actual acts of geopolitical risks. Ideally, it would be interesting to capture if there is varied impact from threats and acts on stock returns and volatility, but we do not have such differentiated data at the level of the emerging countries. Hence, our measure of GPR includes both threats and acts. However, we do have this distinction at the global level and we did conduct analysis based global threats and acts, with the results reported in Footnote 7.

Note that, our choice of these 18 emerging markets is purely driven by the data availability of the GPRs, based on the study of Caldara, Iacoviello, and Markiewitz (2017). And then, in turn, we look to match the GPRs of these countries with their corresponding stock returns. But these 18 countries are clearly the most important emerging countries in the global world and include the BRICS, and have also been susceptible to various forms of geopolitical risks over the last two decades on a regular basis.

Stock returns are computed as the logarithmic first difference of the stock price, that is $R_{i,t} = \log\left(P_{i,t}/P_{i,t-1}\right) * 100, \quad i = 1, ..., N, t = 1, .., T$, where $P_{i,t}$ denotes the stock price of country i at time period t. Data on stock indices in U.S. dollars (to avoid exchange rate impact) are obtained from Datastream of Thomson Reuters.

To ensure a balanced panel, our data covers the monthly period of November 1998 to June 2017, with the end date being driven by the availability of the GPR indices at the time of writing this article, while the start date is due to data availability on stock indices of all the 18 emerging markets.

In Table 1, we present descriptive statistics on the GPRs and the stock returns. As can be seen from Exhibit A of Table 1, the threat-based GPR was on average 95.297 while the country-specific GPR was higher at 102.459. Based on the maximum and minimum values, the threat-based GPR has more extreme values than the other GPRs. This is also confirmed by the standard deviation results; the standard deviation of the threat-based GPR is higher than the other series. All series exhibit positive skewness and excess kurtosis. Hence, the results of the Jarque-Bera test statistics show that the distributions of all GPR metrics, as well as stock returns are non-normal.

Exhibit B of Table 1 reports the per country summary statistics of the GPRs and the corresponding stock market returns. It is revealed in Exhibit B.1 of Table 1 that Ukraine and Turkey have the largest geopolitical risk averages, with values approximately equal to 119. Among the 18 emerging

Table 1. Descriptive statistics.

	Country GPR	Stock Returns	Global GPR	Broad GPR	Narrow GPR	Act GPR	Threat GPR
Exhibit A: Panel data descriptive statistics							
Mean	102.459	0.673	93.582	93.429	94.543	84.606	95.297
Median	95.942	0.987	73.322	81.304	73.204	71.250	74.168
Maximum	311.655	78.905	534.896	353.514	570.343	496.555	604.038
Minimum	20.935	310.634	28.228	45.636	25.344	21.652	23.464
Std. dev.	36.356	11.108	68.047	44.467	71.382	66.156	73.372
Skewness	1.586	5.827	3.374	3.143	3.555	3.686	3.619
Kurtosis	7.317	159.199	18.404	15.908	20.211	20.277	20.831
Jarque-Bera	4821	412173	47520	34634	58263	59284	62219
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4032	4032	224	224	224	224	224

Countries	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Exhibit B: Time series descriptive statistics							
B.1. Country GPR							
Turkey	119.248	111.527	254.029	42.702	41.769	0.770	3.201
Mexico	104.773	100.382	199.919	56.098	22.710	1.049	4.808
Korea	108.642	99.678	282.635	39.237	42.408	1.554	6.256
Russia	108.107	100.529	222.730	52.063	31.520	0.988	3.674
India	92.995	85.035	248.385	55.154	30.442	2.601	11.759
Brazil	100.017	98.399	218.655	47.097	25.247	0.934	5.240
China	102.034	97.322	211.986	65.718	24.488	1.665	6.755
Indonesia	89.231	81.574	289.619	24.804	35.160	1.453	7.313
Saudi Arabia	105.694	105.847	195.457	38.971	29.018	0.369	3.103
South Africa	93.807	93.810	198.871	45.697	26.012	0.691	3.986
Argentina	100.459	96.939	259.228	35.632	34.743	0.942	4.545
Colombia	90.501	88.467	175.845	28.244	28.056	0.593	3.285
Venezuela	101.683	97.125	235.236	42.312	33.974	1.310	5.448
Thailand	102.255	89.886	301.057	44.007	43.385	1.750	6.883
Ukraine	119.725	97.064	311.655	20.935	66.703	1.095	3.366
Israel	93.077	87.919	167.791	46.989	22.019	0.954	3.858
Malaysia	102.522	95.245	284.879	36.712	38.144	1.813	8.197
Philippines	109.487	104.089	216.807	43.797	34.626	0.557	2.985
B.2. Stock market returns							
Turkey	0.582	1.771	54.073	–54.946	13.731	–0.351	5.344
Mexico	0.851	1.141	18.999	–33.958	7.160	–0.635	5.016
Korea	0.883	1.151	26.662	–33.314	8.800	–0.083	4.044
Russia	1.363	2.111	42.456	–42.094	11.254	–0.207	4.788
India	0.843	1.097	32.675	–27.602	8.441	–0.193	3.732
Brazil	0.587	0.920	32.351	–38.586	11.499	–0.377	3.729
China	0.804	1.026	25.570	–33.587	9.495	–0.517	4.413
Indonesia	1.063	1.216	30.421	–52.292	9.569	–0.514	7.320
Saudi Arabia	0.687	1.029	18.744	–27.761	7.268	–0.723	4.776
South Africa	0.477	1.034	16.977	–40.686	7.649	–0.851	5.746
Argentina	0.480	1.474	37.538	–53.452	11.282	–0.796	6.199
Colombia	0.675	0.000	20.763	–28.223	8.289	–0.368	3.289
Venezuela	–0.090	0.334	78.905	–310.63	26.116	–7.597	91.528
Thailand	0.662	1.145	30.841	–39.850	8.601	–0.505	5.999
Ukraine	0.144	–0.053	44.712	–71.140	14.354	–0.724	7.274
Israel	0.765	0.823	16.983	–24.964	6.675	–0.513	4.270

(*Continued*)

Table 1. Descriptive statistics. (Continued)

	Country GPR	Stock Returns	Global GPR	Broad GPR	Narrow GPR	Act GPR	Threat GPR
Malaysia	0.767	1.044	29.441	–19.617	6.031	0.477	6.042
Philippines	0.578	0.925	20.115	–31.435	7.017	–0.546	4.838

Notes: the table reports summary statistics of the country-specific GPR, the Global GPR, the Broad GPR, the Narrow GPR, the Act GPR, the Threat GPR, and the stock market returns. Stock market returns are computed as the logarithmic first differences of the corresponding stock market index, multiplied by a factor of 100. Exhibit B.1. reports the per country summary statistics of the GPR, while Exhibit B.2. reports the per country summary statistics of the stock market returns.

economies, the GPR of Ukraine exhibits the largest fluctuations around its mean, as reflected by the standard deviation and the maximum–minimum values. The higher values of Ukraine's GPR dispersion can be attributed to the ongoing political turmoil that Ukraine experienced during the last decade.

We observe in Exhibit B.2. of Table 1 that the average stock market returns of these emerging economies range from −0.090 (Venezuela) to 1.363 (Russia). As expected, these stock markets exhibit high volatility. For example, six stock markets, namely Turkey, Russia, Brazil, Argentina, Venezuela, and Ukraine, have standard deviations over 10%. We document from maximum and minimum values, that Venezuela has the most disperse stock returns. Almost all stock market returns display negative skewness and excess kurtosis.

As part of preliminary analyses, Table 2 reports the results of both time series and panel data unit root tests for GPRs and the stock market returns. Exhibit A presents the individual time-series based unit root tests and Exhibit B presents the panel data unit root tests. At the time series level, the Augmented Dickey-Fuller (ADF) unit root test is performed, as proposed by Fuller (1976) and Dickey and Fuller (1979, 1981)), using a specification with a constant. We start by fitting an ADF specification of lag length 4 and then we re-estimate the model successively by reducing one lagged difference term at a time. The Akaike Information Criterion is used to determine the most appropriate specification for our data. We observe that for all economies considered, the null hypothesis of non-stationarity of country-specific GPR is strongly rejected, with only exception Ukraine, where the series is found to be non-stationary marginally at level of statistical significance 10%. The same result holds for the other measures of geopolitical risk, as well as the stock market returns.

We consider three panel data unit root tests in Exhibit B, namely Levin, Lin, and Chu (2002), Breitung (2000), and Im, Pesaran, and Shin (2003) tests. The first two tests assume that there is homogeneity in the unit root process for all cross-section units, while their method is based on the estimation of a pooled ADF regression. The third test allow for heterogeneity in the unit root process, while their method is based on the estimation of an individual ADF specification for each cross section unit. Exhibit B reports the *t*-statistics of tests and the corresponding *p*-values. Our results show that the country-specific GPR indices are stationary in levels, since we reject the null hypothesis of unit root at levels of statistical significance 1%, 5%, and 10%.

Econometric Methodology

This section describes the empirical framework adopted to evaluate the impact of GPR measures on mean and variance dynamics of the stock returns. Our approach involves fitting an autoregressive dynamic panel model with a conditional variance-covariance specification to the data. The conditional covariance model evolves as a GARCH process, similar to the one introduced by Cermeño and Grier (2006). The GARCH models are well-known to capture parametrically the stylized fact that variances of asset returns change over time, and large (small) variance changes tend to follow large (small) variance changes. The Autoregressive Conditional Heteroskedasticity (ARCH) class of models were

Table 2. Unit root tests.

Countries	Country GPR	Stock Returns	Global GPR	Broad GPR	Narrow GPR	Act GPR	Threat GPR
Exhibit A: Time series unit root tests							
Turkey	–4.820*** (0.000)	–14.996***(0.000)					
Mexico	–6.285*** (0.000)	–13.254***(0.000)					
Korea	–5.715*** (0.000)	–7.602***(0.000)					
Russia	–5.065*** (0.000)	–12.106***(0.000)					
India	–3.230** (0.018)	–14.157***(0.000)					
Brazil	–6.323*** (0.000)	–13.239***(0.000)					
China	–5.128*** (0.000)	–6.396***(0.000)					
Indonesia	–2.914** (0.043)	–12.469***(0.000)					
Saudi Arabia	–5.532*** (0.000)	–12.151***(0.000)					
South Africa	–5.672*** (0.000)	–14.462***(0.000)					
Argentina	–9.031*** (0.000)	–13.092***(0.000)					
Colombia	–3.272** (0.016)	–9.444***(0.000)					
Venezuela	–4.376*** (0.000)	–13.741***(0.000)					
Thailand	–9.020*** (0.000)	–14.868***(0.000)					
Ukraine	–2.542 (0.105)	–6.644***(0.000)					
Israel	–3.783*** (0.003)	–12.483***(0.000)					
Malaysia	–6.066*** (0.000)	–12.431***(0.000)					
Philippines	–3.276*** (0.000)	–13.777***(0.000)					
			–4.429*** (0.000)	–3.879*** (0.002)	–4.491*** (0.000)	–5.675*** (0.000)	–4.340*** (0.000)

Exhibit B: Panel data unit root tests		
Methods	Country GPR	Stock Returns
Levin, Lin, and Chu 2002	–11.062*** (0.000)	–12.207*** (0.000)
Breitung 2000	–-6.733*** (0.000)	–14.381*** (0.000)
Im, Pesaran, and Shin 2003	–13.033*** (0.000)	–22.402*** (0.000)

Notes: Exhibit A reports the results of the Augmented Dickey-Fuller (ADF) test corresponding to a specification with intercept. The backward elimination is used to determine the lag truncation with maximum lag order equal to 4, while the Akaike Information Criterion is implemented to compare the models. Exhibit B reports the results of the panel data unit root tests. The test statistics of three test procedures are reported: Levin, Lin, and Chu (2002), Breitung (2000), and Im, Pesaran, and Shin (2003). The *p*-values of the *t*-statistics are in parentheses. * indicates statistical significance at level 10%; ** indicates statistical significance at levels 5% and 10%; *** indicates statistical significance at levels 1%, 5%, and 10%.

originally introduced by Engle (1982) and then generalized by Bollerslev (1986). Our method is summarized below.

Consider the vector of stock returns $R_{i,t} = \left(R_{1,t}, R_{2,t}, ..., R_{N,t}\right)'$, $t = 1,2,\ldots,T$, $i = 1,2,\ldots,N$, where T and N represent the number of time periods and cross-sectional units (in our case, the 18 emerging economies), respectively. Mean dynamics can be estimated by an autoregressive model of order p, denoted as AR(p):

$$R_{i,t} = a_i + \sum_{k=1}^{p} \beta_k R_{i,t-k} + \gamma_1 GPR_{i,t} + u_{i,t}, \tag{1}$$

where a_i denotes the constant of the panel regression, $\beta_k, k = 1, ..., p$ denote the coefficients of the autoregressive terms $R_{i,t-k}, k = 1, ..., p$, and γ_1 measures the impact of $GPR_{i,t}$ on the mean dynamics of the stock returns. It is assumed that all the characteristic roots of the lag polynomial $\left(1 - \beta_1 L - ..., \beta_p L^p\right) = 0$ falls inside the unit circle. This condition ensures that the autoregressive process described in Equation (1) is stable, and as a consequence we have a stationary panel. If the autoregressive process is stationary, then any shocks have a transitory effect on the dynamic behavior of the system and their impact disappears in time. Thus the first two moments of the AR process will be time-invariant. In the literature of financial and economic data analysis, the null hypothesis that the AR process contains one unit root is tested in order to infer whether the process is stationary or not. We discuss the implementation of several time series- and panel data-based unit root tests applied to the variables of interest. Equation (1) can be estimated by ordinary least squares, allowing for a single intercept in the model (pooled regression), or by including one constant for each emerging market to control for inter-individual heterogeneity (fixed effects regression) in the conditional mean of the stock returns across the countries.

If $u_{i,t} = \left(u_{1,t}, u_{2,t}, ..., u_{N,t}\right)'$ is the vector of residuals obtained from model (1), with $u_{i,t}/\psi_{t-1} \sim N(0, \Sigma_t)$, where ψ_{t-1} is the information set available at time $t-1$, then the variance-covariance matrix Σ_t is allowed to be time-dependent, as it is based on the information set available till the previous year.

The diagonal elements of Σ_t are the conditional variances which are given by

$$\sigma_{i,t}^2 = k_i + \theta_1 \sigma_{i,t-1}^2 + \phi_1 u_{i,t-1}^2 + \delta_1 GPR_{i,t},\ i = 1, ..., N \tag{2}$$

while the conditional covariances-the off-diagonal elements of Σ_t- are given by

$$\sigma_{ij,t} = l_{ij} + n_1 \sigma_{ij,t-1} + m_1 u_{i,t-1} u_{j,t-1},\ i \neq j \tag{3}$$

According to Equations (2) and (3), the conditional variance and covariance processes have a GARCH (1,1) representation. The coefficient $\delta_1$measures the effect of $GPR_{i,t}$ on the variance dynamics of the stock returns.

Model (1) can be rewritten in matrix form:

$$\mathbf{R}_t = \boldsymbol{\beta}_\mathbf{0} + \boldsymbol{\beta} \mathbf{R}_{t-p} + \mathbf{u}_t, \quad t = 1, ..., T \tag{4}$$

where $\mathbf{R}_t, \boldsymbol{\beta}_\mathbf{0}$ and $\mathbf{u}_t$ are ($N \times 1$)-dimensional vectors of the stock returns, the constant, and the disturbance term respectively, while $\mathbf{R}_{t-p} = \left[R_{i,t-1}, ..., R_{i,t-p}, GPR_{i,t}\right]$and $\boldsymbol{\beta} = \left[\beta_1, .., \beta_p, \gamma_1\right]'$.

The log-likelihood function of the panel AR(p) regression model with GARCH type errors is given by the following equation:

$$LogL = -\frac{1}{2}NT\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T}\left(\mathbf{R}_t - \boldsymbol{\beta}_\mathbf{0} - \boldsymbol{\beta}\mathbf{R}_{t-p}\right)'\Sigma_t^{-1}\left(\mathbf{R}_t - \boldsymbol{\beta}_\mathbf{0} - \boldsymbol{\beta}\mathbf{R}_{t-p}\right) \quad (5)$$

The parameters ofboth conditional mean and conditional variance-covariance specifications are estimated by maximizing the log-likelihood function presented in Equation (5). Numerical methods are used to maximize Equation (5). Under regularity conditions, the maximum likelihood estimator is shown to be consistent, asymptotically efficient and asymptotically distributed as normal. In this regard, we also note that the true parameter vector corresponds to the mean and the inverse of the information matrix relates to the variance-covariance matrix. Using this result, we can approximate the asymptotic covariance-variance matrix of the maximum likelihood estimator by the inverse of the Hessian of the log-likelihood function evaluated at the parameter estimates.

Empirical Results

Misspecification Tests

It is of great importance to perform a battery of diagnostic tests as a preliminary analysis in order to identify the most suitable conditional mean and conditional variance-covariance model parameterization of our data. The panel AR-GARCH model involves the simultaneous modeling of mean and variance-covariance dynamics, and therefore it faces dimensionality problems due to the large number of parameters to be estimated. A well specified parametric model ensures accurate coefficient estimates and reliable statistical inference.

The first step is to test for individual heterogeneity in the conditional mean by using a different constant for each economy but the same slope coefficients of the regression. To test for the absence of individual heterogeneity, we estimate model (1) by fixed effects, and then we evaluate the statistical significance of the cross-section dummy variables coefficients via an F-test. Table 3 reports that the null hypothesis $H_0 : a_i = a$ of individual homogeneity cannot be rejected, and therefore the panel data are poolable. However, if the residuals exhibit conditional heteroskedasticity, then the OLS estimator of model (1) is consistent but not efficient. In this case, there is an amount of uncertainty about the reliability concerning the OLS coefficient estimates and the resulting sums-of-squares of the regression used to calculate the F-test. Consequently, the F-test results may lead to misleading conclusions. Therefore, individual effects in the conditional mean are also tested by calculating robust standard errors of model (1) using Arellano's (1987) heteroskedasticity and autocorrelation consistent covariance (HAC) estimator.[4] The results of the Wald test also show strong support of the null hypothesis of no individual effects. Nevertheless, model (1) is estimated both with fixed effects and without (pooled regression model).

Subsequently, it is essential to test for the presence of serial correlation in the residuals of the models, because if such effects are left unaccounted for, there may be misleading inference on the presence of time variation in the conditional variance-covariance process. Following Wooldridge (2002), a pooled regression model is fitted to the data using the stock returns as the dependent variable, and GPR and lagged values of the residuals as the independent variables. Then, a standard t-test is used to examine the statistical significance of the coefficient of each lagged residual. Six lagged error terms are used in the regression while HAC standard errors are estimated to ensure robustness. Our findings demonstrate that there is no support of the null hypothesis of no serial correlation up to the first three lags. Therefore, an autoregressive model of third order appears to be the most correct parameterization of the conditional mean equation.

The next step is to investigate the existence of significant cross-sectional independence in the sense that $\sigma_{ij} = 0$ for two different cross-sectional units. The presence of CD of the error term would require the use of the log-likelihood function presented in Equation (5). In the opposite case, where cross-sectional independence holds, a reduced form of the log-likelihood function can be used for the

Table 3. Misspecification tests.

Exhibit A: Conditional mean diagnostic tests					
Individual Effects $H_0 : a_i = a$	**0.143 (0.999)**	**Individual effects with HAC**	**0.104 (0.999)**		
Serial correlation					
$H_0 : \rho(1) = 0$	$H_0 : \rho(2) = 0$	$H_0 : \rho(3) = 0$	$H_0 : \rho(4) = 0$	$H_0 : \rho(5) = 0$	$H_0 : \rho(6) = 0$
2.968*** (0.009)	1.478 (0.157)	3.497*** (0.003)	–0.197 (0.846)	–0.197 (0.846)	–0.314 (0.756)
Exhibit B: Conditional variance-covariance diagnostic tests					
Cross-sectional independence	51.336 (0.000)				
Heteroskedasticity across time					
$u^2_{i,t-1}$	0.037* (0.068)				
$u^2_{i,t-2}$	0.008 (0.684)				
$u^2_{i,t-3}$	0.005 (0.826)				
$u^2_{i,t-4}$	–0.006 (0.792)				
$u_{i,t-1}u_{i,t-2}$	0.175 (0.374)				
$u_{i,t-1}u_{i,t-3}$	0.303 (0.133)				
$u_{i,t-2}u_{i,t-3}$	–0.044 (0.824)				
$u_{i,t-2}u_{i,t-4}$	0.006 (0.977)				
$u_{i,t-3}u_{i,t-4}$	0.437** (0.023)				
$u_{i,t-1}u_{i,t-4}$	0.625*** (0.003)				
Individual effects in variance $H_0 : k_i = k$	1.788** (0.024)				

Notes: Exhibit A reports the results of the diagnostic tests of the conditional mean. Individual effects refer to testing for the presence of individual homogeneity in the conditional mean;we report the value of the *F*-test and the corresponding *p*-value in parenthesis.Individual effects with HAC refer to testing for the presence of individual homogeneity by using a Wald test based on HAC standard errors. Serial correlation refers to Wooldridge's (2002) test for the presence of serial dependence in the residuals of the conditional mean; we report the values of the *t*-statistics and the corresponding *p*-values in parentheses. Exhibit B presents the results of the diagnostic tests of the conditional variance and conditional covariance. Cross-sectional independence refers to Pesaran's (2004) test on the presence of cross-section independence; we report the value of the test statistic and the corresponding *p*-value in the parenthesis. Heteroskedasticity across time refers to an AR(4) model of squared residuals and cross products of lagged residuals. We report the coefficient estimates and the corresponding *p*-values. Individual effects in variance refer to testing for the presence of individual homogeneity in the conditional variance; we report the *F*-test value and the corresponding *p*-value. * indicates statistical significance at level 10%; ** indicates statistical significance at levels 5% and 10%; *** indicates statistical significance at levels 1%, 5%, and 10%.

estimation of a diagonal conditional variance-covariance matrix. Pesaran's (2004) CD test is implemented to examine the null hypothesis $H_0 : \sigma_{ij} = 0$ to the residuals of Equation (1). The statistic and the associated p-values (presented in parentheses) decisively reject the null hypothesis of cross-sectional independence of the residuals, providing strong evidence of cross-sectional correlation. This finding indicates that the use of the log-likelihood function of the Equation (5) is more appropriate for our panel data.

Next, regarding heteroskedasticity across time t, we follow Cermeño and Grier (2006) and we retain the residuals from a pooled AR(12) regression of the stock returns. Then, the squared residuals are regressed against the lagged values of the squared residuals, and all two-way interactions (cross products) between the lagged residuals. A four lag structure is used in the autoregressive specification of the squared residuals and the cross products of the residuals. A standard t-test is performed on each coefficient of past squared residual and cross product in order to investigate for the presence of autoregressive conditionally heteroskedasticity effects (ARCH) and time-dependence in the conditional covariance specification of the data, respectively. The presence of ARCH effects implies that the variance of the data depends on its past history, and it evolves in time as an autoregressive process. If these effects are present and they are left unaccounted for parametrically, then inference on the regression coefficients of the conditional mean model will be misleading. Panel B of Table 1 reports the estimated coefficients of the parameters and the p-values of the corresponding t-tests. The results show that we only reject the null hypothesis of no first order ARCH effects at level of statistical significance 10%. Furthermore, two cross products of residuals are found to be statistical significant at level 5%, providing evidence that the null hypothesis $H_0 : \sigma_{ij,t} = \sigma_{ij}$ does not hold, and hence, the conditional covariance process is time dependent.

The next test involves investigating for the presence of individual homogeneity in the variance process: the previous model is estimated by fixed effects and the statistical significance of the cross-section dummy variables coefficients are tested using an F-test. We find that there is no strong support of the null hypothesis of individual homogeneity in the variance$H_0 : k_i = k$, and as a consequence, individual specific intercepts must be included in Equation (2). Overall, misspecification tests based on the regression of the squares residuals and the cross products indicate that the conditional variance and conditional covariances evolve as a GARCH(1,1) process, while individual heterogeneity in the variance must be modeled.

Estimation Results

Table 4 reports the results of the estimated models when using country-specific GPR in both the conditional mean and conditional variance-covariance specifications. Exhibit A presents the estimated coefficients, as well as the corresponding p-values in the parentheses, of the conditional mean specification parameters, given by Equation (1). Exhibit B reports the estimated coefficients and the corresponding p-values (in parentheses) of the conditional variance specification, given by Equation (2).[5] Model A represents the AR (3) model of stock returns with country-specific GPR allowing for cross-section fixed effects, and model B represents the same AR (3) specification estimated by means of a pooled regression. Both specifications have a GARCH (1,1) conditional variance-covariance representation, including a country-specific GPR term. The models are estimated by the method of maximum likelihood described.[6]

We observe that in all conditional mean specifications reported in Exhibit A, the first and third autoregressive coefficients are statistically significant at level 1%.On the other hand, the coefficient of country-specific GPR variable is found to be statistically insignificant, even though it does possess the correct sign (Caldara and Iacoviello 2017). For instance, when models are estimated by including country dummy variables (fixed effects), the estimated coefficient of country-specific GPR is −0.016 with a corresponding p-value 0.753. Therefore, our evidence suggests that country-specific GPR does not affect the conditional mean of stock returns. This finding is robust to conditional mean specifications that allow for cross-section heterogeneity and cross-section homogeneity, respectively.

Table 4. Estimation results of the country-specific and global GPR based models.

Models	Country GPR with fixed effects (A)	Country GPR without fixed effects (B)	Global GPR with fixed effects (C)	Global GPR without fixed effects (D)
Exhibit A: Conditional mean specification				
Constant	0.691 (0.198)	0.724 (0.166)	0.650** (0.029)	0.648** (0.030)
$R_{i,t-1}$	0.111*** (0.000)	0.112*** (0.000)	0.112*** (0.000)	0.113*** (0.000)
$R_{i,t-2}$	0.023 (0.161)	0.023 (0.152)	0.023 (0.161)	0.023 (0.152)
$R_{i,t-3}$	0.048*** (0.003)	0.048*** (0.002)	0.047*** (0.003)	0.048*** (0.003)
$GPR_{i,t}$	–0.016 (0.753)	–0.019 (0.694)		
$GGPR_t$			–0.013 (0.623)	–0.013 (0.625)
Exhibit B: Conditional variance specification				
Turkey	6.393*** (0.008)	6.209*** (0.008)	7.090*** (0.002)	6.955*** (0.002)
Mexico	1.340 (0.143)	1.302 (0.161)	2.190*** (0.003)	2.129*** (0.004)
Korea	1.472 (0.154)	1.377 (0.169)	2.177** (0.013)	2.113** (0.014)
Russia	4.548*** (0.004)	4.319*** (0.005)	5.221*** (0.000)	5.026*** (0.000)
India	3.116** (0.015)	3.015** (0.016)	3.706*** (0.002)	3.631*** (0.002)
Brazil	7.548*** (0.000)	7.386*** (0.000)	8.105*** (0.000)	7.973*** (0.000)
China	3.971*** (0.006)	3.859*** (0.006)	4.615*** (0.006)	4.534*** (0.001)
Indonesia	2.989*** (0.006)	2.850*** (0.007)	3.450*** (0.001)	3.334*** (0.001)
Saudi Arabia	1.234 (0.216)	1.158 (0.235)	2.004** (0.011)	1.966** (0.011)
South Africa	2.431** (0.020)	2.359** (0.021)	3.042*** (0.001)	2.995*** (0.001)
Argentina	5.889*** (0.000)	5.740*** (0.000)	6.505*** (0.000)	6.384*** (0.000)
Colombia	2.925** (0.013)	2.829** (0.014)	3.496*** (0.002)	3.423*** (0.002)
Venezuela	67.596*** (0.000)	68.223*** (0.000)	65.829*** (0.000)	66.397*** (0.000)
Thailand	2.308** (0.042)	2.191** (0.046)	2.943*** (0.004)	2.856*** (0.005)
Ukraine	9.861*** (0.000)	9.621*** (0.000)	10.469*** (0.000)	10.237*** (0.000)
Israel	0.957 (0.256)	0.883 (0.282)	1.622** (0.015)	1.579** (0.017)
Malaysia	0.299 (0.715)	0.238 (0.762)	1.106** (0.047)	1.077* (0.050)
Philippines	1.461 (0.128)	1.354 (0.146)	2.178*** (0.006)	2.109*** (0.007)
GARCH	0.848*** (0.000)	0.849*** (0.000)	0.851*** (0.000)	0.853*** (0.000)
ARCH	0.086*** (0.000)	0.085*** (0.000)	0.085*** (0.000)	0.084*** (0.000)
$GPR_{i,t}$	0.131* (0.095)	0.135* (0.077)		
$GGPR_t$			0.050 (0.220)	0.050 (0.211)
Log-likelihood	–136390000	–136420000	–136390000	–136420000

Notes: the table presents the estimation results of the mean and variance specifications of models A and B, respectively. Exhibit A presents the estimation results of the conditional mean equation, and Exhibit B presents the results of the conditional variance equation. The conditional mean equation of models A and B is specified as $R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{i,t-1} + \beta_{i,2}R_{i,t-2} + \beta_{i,3}R_{i,t-3} + \beta_{i,4}GPR_{i,t} + u_{i,t}$, where $R_{i,t}$ denotes the logarithmic stock returns of countries i = Turkey,. . .,Philippines, for the time period (t) between 11/1998 and 12/2016, while $GPR_{i,t}$ denotes the country-specific GPR factor. Model A is estimated as a panel regression with fixed effects while model B is estimated as a pooled regression. The conditional variance equation of each model is specified as $\sigma^2_{i,t} = k_i + \theta_1\sigma^2_{i,t-1} + \phi_1 u^2_{i,t-1} + \delta_1 GPR_{i,t},\ i = 1, ..., N$; the conditional covariance equation is specified as $\sigma_{ij,t} = l_{ij} + n_1\sigma_{ij,t-1} + m_1 u_{i,t-1}u_{j,t-1},\ i \neq j$.
The conditional mean equation of models C and D is specified as $R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{i,t-1} + \beta_{i,2}R_{i,t-2} + \beta_{i,3}R_{i,t-3} + \beta_{i,4}GGPR_t + u_{i,t}$, where $GGPR_t$ denotes the global GPR factor. Model C is estimated a panel regression with fixed effects while model D is estimated as a pooled regression. The conditional variance equation of each model is specified as $\sigma^2_{i,t} = k_i + \theta_1\sigma^2_{i,t-1} + \phi_1 u^2_{i,t-1} + \delta_1 GGPR_t,\ i = 1, ..., N$; the conditional covariance equation is specified as $\sigma_{ij,t} = l_{ij} + n_1\sigma_{ij,t-1} + m_1 u_{i,t-1}u_{j,t-1},\ i \neq j$. *p*-values are in parentheses.
* indicates statistical significance at level 10%; ** indicates statistical significance at levels 5% and 10%; *** indicates statistical significance at levels 1%, 5%, and 10%.

Let us examine now the estimation results of the conditional variance specifications (exhibit B) of Table 4. Most of the individual specific intercepts in the conditional variance equations A and Bare found to be statistically significant. In particular, the individual variances of Mexico, Korea, Israel, Malaysia, and Philippines are statistically insignificant, while the remaining 15 variances are significant. The variances range from 0.299 (Malaysia) to 67.596 (Venezuela), with the majority of these stock markets having high degree of stock return variability around their means, a typical feature of riskiness of the emerging stock markets.

The coefficients of ARCH and GARCH terms are also found to be statistically significant. The presence of ARCH effect confirms the appropriateness of a GARCH based variance-covariance model structure for our data. The volatility is highly persistent but stationary since the sum of the ARCH and GARCH parameter coefficients are always close to one (i.e., approximately equal to 0.9). This result is consistent with earlier findings on the high persistence of stock return volatility; see Lamoureux and Lastrapes (1990), Hamao, Masulis, and Ng (1990), Ding, Granger, and Engle (1993) among others. The log-likelihood values suggest that the model B must be preferred over model A. This finding confirms the evidence of the presence of poolability of the data derived from the individual effects tests in the conditional mean equation reported earlier. We observe that the coefficient of country-specific GPR variable in the variance equation is statistically significant only at the10% level. The value of the coefficient is large and positive, with a one-unit increase (decrease) in GPR increasing (reducing)the conditional variance of the stock returns by more than 0.13 units, with this result holding for both models A and B. Therefore, although country-specific GPR does not have an impact on the stock returns, it does have a positive effect on the stock returns volatility (though statistically weak); with the latter result being in line with the literature on terror attacks and global GPRs on financial markets as discussed in the introduction.

In Table 4, under panels C and D, we repeat the analysis above, but now using the global GPR. Interestingly now, the global GPR index fails to have any significant effect even at the 10% level on volatility, unlike the country-specific GPRs, though global GPR does reduce stock returns and increase volatility. This result is in contradiction with the time-series based analyses involving global GPR and equity markets which we covered in the introduction.[7] However, as shown in Table 5 (panels A and B), using the so-called "broad" global GPR index (BGPR), where by Caladara and Iacoviello (2017) combines the search terms with bigrams that a machine learning algorithm signals as very likely indicators of rising geopolitical tensions, we were able to obtain statistically significant increases in volatility, though no effect is observed for returns. In fact the effect on volatility from the BGPR is not only economically stronger than that obtained under the country-specific GPRs (with a coefficient of 0.153 relative to 0.131 or 0.135), but is also statistically significant at the conventional 5% level. But, just like the overall global GPR, the narrow version of the global GPR (NGPR), which in turn is based on the identification of bigrams that are more likely than not to appear in set of articles that contains false positives, and then by excluding all the articles containing any of these bigrams from the benchmark global index (Caladara and Iacoviello, 2017), have no significant impact on both returns and volatility (panels C and D in Table 5). The results derived under the BGPR is now more in line with the existing literature, and also importantly highlights the fact that a refined broad measure of global GPR, i.e., the BGPR (which combines the search terms with bigrams of signals as very likely indicators of rising geopolitical tensions) has a stronger influence on volatility than country-specific GPRs. This result is not surprising given the globalized nature of modern financial markets, where world shocks are likely to have bigger influence than domestic ones. This finding however, in some sense contrast those of Fernández and Lucey (2008), who finds importance of domestic economic and political events for breaks in stock market volatility. But it must be realized that their data sample ended in 2006, and that of ours ends in 2017, and clearly over the last decade the integration of emerging markets with the global economy has indeed intensified more.

Based on the suggestions of an anonymous referee, we conduct three additional analyses: (a) A pure time-series model is estimated for each country to analyze the impact of geopolitical risks on returns and volatility; (b) In order to control for possible over-parameterization of the model, we re-

Table 5. Estimation results of the broad and narrow GPR based models.

Models	Broad GPR with fixed effects (A)	Broad GPR without fixed effects (B)	Narrow GPR with fixed effects (C)	Narrow GPR without fixed effects (D)
Exhibit A: Conditional mean specification				
Constant	0.601 (0.139)	0.599 (0.139)	0.650** (0.026)	0.648** (0.026)
$R_{i,t-1}$	0.112*** (0.000)	0.113*** (0.000)	0.112*** (0.000)	0.113*** (0.000)
$R_{i,t-2}$	0.023 (0.156)	0.023 (0.147)	0.023 (0.161)	0.023 (0.152)
$R_{i,t-3}$	0.048*** (0.003)	0.048*** (0.002)	0.047*** (0.003)	0.048*** (0.003)
$BGPR_t$	–0.007 (0.849)	–0.007 (0.851)		
$NGPR_t$			–0.012 (0.609)	–0.012 (0.611)
Exhibit B: Conditional variance specification				
Turkey	6.329*** (0.005)	6.219*** (0.005)	7.207*** (0.002)	7.073*** (0.002)
Mexico	1.353* (0.091)	1.303* (0.099)	2.293*** (0.002)	2.230*** (0.002)
Korea	1.313 (0.154)	1.260 (0.165)	2.288*** (0.009)	2.221** (0.010)
Russia	4.380*** (0.003)	4.197*** (0.004)	5.332*** (0.000)	5.136*** (0.000)
India	2.847** (0.021)	2.782** (0.023)	3.812*** (0.002)	3.730*** (0.002)
Brazil	7.282*** (0.000)	7.171*** (0.000)	8.215*** (0.000)	8.073*** (0.000)
China	3.729*** (0.006)	3.663*** (0.006)	4.723*** (0.006)	4.643*** (0.000)
Indonesia	2.590** (0.016)	2.486** (0.019)	3.558*** (0.000)	3.442*** (0.001)
Saudi Arabia	1.000 (0.255)	0.973 (0.265)	2.130*** (0.007)	2.087*** (0.007)
South Africa	2.139** (0.028)	2.105** (0.029)	3.151*** (0.001)	3.103*** (0.000)
Argentina	5.687*** (0.000)	5.584*** (0.000)	6.608*** (0.000)	6.486*** (0.000)
Colombia	2.513** (0.029)	2.456** (0.030)	3.614*** (0.001)	3.539*** (0.001)
Venezuela	65.488*** (0.000)	66.099*** (0.000)	66.141*** (0.000)	66.697*** (0.000)
Thailand	2.037* (0.052)	1.965* (0.056)	3.055*** (0.003)	2.965*** (0.004)
Ukraine	9.499*** (0.000)	9.300*** (0.000)	10.618*** (0.000)	10.372*** (0.000)
Israel	0.746 (0.322)	0.710 (0.342)	1.718*** (0.009)	1.672** (0.011)
Malaysia	0.228 (0.725)	0.209 (0.743)	1.205** (0.031)	1.172** (0.034)
Philippines	1.289 (0.126)	1.233 (0.136)	2.286*** (0.004)	2.213*** (0.005)
GARCH	0.850*** (0.000)	0.852*** (0.000)	0.851*** (0.000)	0.853*** (0.000)
ARCH	0.085*** (0.000)	0.084*** (0.000)	0.085*** (0.000)	0.084*** (0.000)
$BGPR_t$	0.153** (0.021)	0.153** (0.020)		
$NGPR_t$			0.039 (0.308)	0.040 (0.294)
Log-likelihood	–136370000	–136400000	–136400000	–136430000

Notes: the table presents the estimation results of the mean and variance specifications of models A to D, respectively. Exhibit A presents the estimation results of the conditional mean equation, and Exhibit B presents the results of the conditional variance equation. The conditional mean equation of models A and B is specified as $R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{i,t-1} + \beta_{i,2}R_{i,t-2} + \beta_{i,3}R_{i,t-3} + \beta_{i,4}BGPR_t + u_{i,t}$, where $R_{i,t}$ denotes the logarithmic stock returns of countries i = Turkey,. . .,Philippines, for the time period (t) between 11/1998 and 12/2016, while $BGPR_t$ denotes the broad GPR factor. Model A is estimated as a panel regression with fixed effects while model B is estimated as a pooled regression. The conditional mean equation of models C and D is specified as $R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{i,t-1} + \beta_{i,2}R_{i,t-2} + \beta_{i,3}R_{i,t-3} + \beta_{i,4}NGPR_t + u_{i,t}$, where $NGPR_t$ denotes the narrow GPR factor. Model C is estimated a panel regression with fixed effects while model D is estimated as a pooled regression. The conditional variance equation of each model is specified as $\sigma^2_{i,t} = k_i + \theta_1\sigma^2_{i,t-1} + \phi_1 u^2_{i,t-1} + \delta_1 GPR_{i,t},\ i = 1,\ldots,N$; the conditional covariance equation is specified as $\sigma_{ij,t} = l_{ij} + n_1\sigma_{ij,t-1} + m_1 u_{i,t-1}u_{j,t-1},\ i \neq j$. *p*-values are in parentheses.* indicates statistical significance at level 10%; ** indicates statistical significance at levels 5% and 10%; *** indicates statistical significance at levels 1%, 5%, and 10%.

estimate the panel-GARCH model with the same constant for each country in the conditional variance equation, and; (c) Re-conduct the panel-GARCH estimations, by categorizing countries into regions. In general, our results were found to be qualitatively similar to those reported in the article (see the Supplementary Material, available online).

Conclusions

In this article, we analyze the role of country-specific and GPRs on the returns and volatility of 18 emerging market economies (Turkey, Mexico, Korea, Russia, India, Brazil, China, Indonesia, Saudi Arabia, South Africa, Argentina, Colombia, Venezuela, Thailand, Ukraine, Israel, Malaysia, and Philippines) over the monthly period of 1998:11 to 2017:06. For our purpose, we use a panel GARCH approach, which offers substantial efficiency gains in estimating the conditional variance and covariance processes by accounting for interdependencies and heterogeneity across economies, besides the fact that we are also able to capture possible CD, unlike in a time series-based GARCH model. Based on the panel GARCH model, we find that, while country-specific GPRs do not have an impact on stock returns, it does have a positive, but statistically weak effect on equity market volatility. But when we consider a refined broad measure of global GPR, though there is still no significant effect on returns, the impact on volatility is both economically and statistically stronger than that obtained under the country-specific GPRs, highlighting the dominance of world rather than domestic shocks in affecting globalized equity markets of the emerging economies.

Our results have important implications for academicians, investors and policymakers. Note that, if the effect of GPRs on only returns was analyzed ignoring the effect on volatility, the academic would wrongly conclude that the equity markets of these 18 emerging countries are weakly efficient relative to geopolitical events. As is well-known, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices. Also, to price an option, one needs reliable estimates of the volatility of the underlying assets. Moreover, financial risk management according to the Basle Accord as established in 1996 also requires modeling of volatility as a compulsory input to risk-management for financial institutions around the world. Given that GPRs, especially global GPR, tends to affect stock market fluctuations, investors and financial managers need to incorporate the information content of geopolitical events in the models that they use to compute volatility. Finally, policy makers concerned with the impact of equitymarket volatility on the real economy, should be ready to undertake appropriate measures (for instance monetary policy easing and/or fiscal expansion) to circumvent the negative effects associated with heightened stock market uncertainty following increases in GPRs. Overall, our results highlight the need to go beyond first-moment effects of GPRs on stock markets, and analyzethe impact on higher (second)-moments, via the usage of appropriate econometric models that allows one to look at volatility, besides returns. As part of future analysis, it would be interesting to analyze whether one could use the panel GARCH model to forecast stock returns and volatility based on information from GPRs, since in-sample predictability does not necessarily guarantee the same over an out-of-sample.

Acknowledgments

We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

Notes

1. See http://www.businesswire.com/news/home/20170613005348/en/.
2. The data can be freely downloaded from: https://www2.bc.edu/matteo-iacoviello/gpr.htm.
3. A monthly reading of 100 corresponds to about 350 articles per month containing terms related to geopolitical risk.
4. Arellano's (1987) estimator is a panel version of White's (1980) and Newey and West's (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) estimator.

5. The estimates of conditional covariance specification (Equation (3)) are available upon request from the authors.

6. Note that, the GPR observations are divided by 10 to help the optimization procedure of the maximum likelihood estimation.

7. Note that, Caldara and Iacoviello (2017) further disentangle the direct effect of adverse global geopolitical events from the effect of pure geopolitical risks by constructing two indexes: The Geopolitical Threats index (GPRT), which only includes words belonging to Search groups 1 to 4 (discussed above in the Data segment), and the Geopolitical Acts index (GPRA) only includes words belonging to Search groups 5 and 6 (discussed in the Data section of the article). We observed that GPRT (GPRA) significantly reduced (increased) returns and volatility. This result possibly provides the underlying reason as to why the global aggregate GPR fails to have any significant effect on returns and volatility, with the effects of GPRT and GPRA cancelling each other out. Complete details of these results are available upon request from the authors.

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