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Geopolitical risks and financial stress in emerging economies

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Abstract

We investigate the impacts of geopolitical risks (GPRs) on financial stress (FS) in major emerging economies from 1985 to 2019. Applying a recently developed panel quantile estimation method, we show that GPRs pose serious risks to the stability of the financial condition in emerging economies. Namely, when FS is already equal to or above average, GPRs intensify this instability to a remarkable degree. Nevertheless, GPRs do not ignite the stress when the financial situation is benign. In emerging economies, foreign exchange markets and, to a lesser extent, the banking industry and the debt market suffer more severe consequences of geopolitical tensions than the stock market. In contrast, advanced economies, represented by the Group of Seven (G7), have witnessed detrimental consequences of GPRs on their stock markets, but negligible effects on other parts of their financial systems.

KEYWORDS

banking sector, debt market, emerging economies, financial stress, foreign exchange market, geopolitical risks, stock market

1 | INTRODUCTION

Ushering in an era of great uncertainty, geopolitical risks (GPRs) represent some of the most dangerous threats to the global economy. They are considered seriously threaten the stability of the world on many fronts, including economics, politics, and technology (The Economist, 2022). These risks can emerge from a wide range of events, both local and global: from the Russo-Ukrainian War, terrorist attacks, trade disputes, and political gridlock, to climate change, cyberattacks, technology decoupling, and the COVID-19 pandemic (Blackrock Investment Institute, 2023). Given the increasingly integrated nature of the world, geopolitical threats can quickly accelerate on a global scale and spread their huge consequences. Understanding the ramifications of geopolitical turmoil on emerging economies is of great interest to many academic, political, and business circles. This article aims to investigate the extent to which the financial stress (FS) in emerging economies can be attributed to geopolitical uncertainties. For a comparison, we also conduct a similar analysis on G7 economies.

GPRs have received considerable attention from policymakers and businesses. Mark Carney, the Governor of the Bank of England, argues that GPRs are one of three components of 'the uncertainty trinity' in the macroeconomy (Carney, 2016). Jerome Powell, the 16th Chair of the Federal Reserve, lists GPRs as one of the major challenges in implementing monetary policies in the US (Powell, 2019). The International Monetary Fund (IMF) and the World Bank (WB) have repeatedly identified geopolitical tensions as an important source of instability across the globe (see e.g. IMF, 2017–2023, World Bank, 2021). And monitoring GPRs has become a fixture in the business agendas of many financial companies, newspapers, and consultancy firms, among others, McKinsey (2016), Morgan (2019), Blackrock Investment Institute (2023), and The Economist (2022).

Multiple efforts have been made in the empirical literature to examine the influence of GPRs on certain areas of the financial environments of emerging economies. Among these efforts, three major issues have been identified. First, how can GPRs and FS be properly and systematically measured at a high frequency? Second, how can the typical features of long financial time series in examining the impacts of GPRs be accounted for? Third, how can we provide not only a comprehensive picture of the impacts of GPRs on the whole financial system but also on the subsectors of the financial system?

Using monthly data from 1985 to 2019 for 17 major emerging economies, we attempt to address all these issues. We point out that GPRs have pronounced impacts on a global scale. In general, heightened GPRs aggravate stress in financial systems. The impacts are diverse, depending on the subsectors affected, the severity of FS, and the countries being examined. These findings will aid in monitoring global financial markets, managing and preparing for macro risks, and making investment decisions in both normal and turbulent times, all of which have become serious concerns given that geopolitical uncertainties are becoming more complex, interregional, contagious, and increasingly unpredictable.

Our paper is divided into five parts. Following this introduction, Section 2 briefly reviews the literature on GPRs, FS, and the connection between the two. Sections 3 and 4 present our data, model, and estimation results. Finally, Section 5 concludes.

2 | LITERATURE REVIEW

Our research topic pertains to the literature on the consequences of terrorist attacks, wars, conflicts (Eckstein & Tsiddon, 2004) and rare disasters (Barro, 2006). The approach of Eckstein and Tsiddon (2004) is an extension of the Blanchard-Yaari model (Blanchard & Fischer, 1989). Eckstein and Tsiddon (2004) argue that terror shortens life expectancy and increases the life uncertainty of citizens. Governments react to the consequences of terror by increasing their defense spending, but the amounts they spend cannot offset the damages yielded by terror. As a result, terror reduces investment, output, and consumption. The rare macroeconomic disasters model developed by Barro (2006) resolves the asset-pricing puzzles. Wars are rare disasters that occur infrequently but which can nevertheless cause tremendous harm to the macroeconomy. The huge drops in consumption that accompany such disasters help to explain the dynamics of many financial asset prices and risk premiums over time, such as stocks, real estates, T-bills, exchange rates, and options.

The empirical studies conducted in this area provide extensive evidence that geopolitical challenges are a key source of fluctuations in worldwide financial markets. A descriptive study by Ferguson (2008) demonstrates that wars severely affect GDP, consumer prices, exchange rates, inflation, commodity prices, and long-term bond yields in Germany, Russia, the UK, and the US. Baur and Smales (2020) find that stock and bond markets respond adversely to GPRs, but precious metals are resilient when faced with geopolitical challenges. Balcilar et al. (2018) argue that GPRs drive stock market volatility rather than returns for the BRICS economies. Several studies note that geopolitical turbulence can affect financial conditions indirectly through output, investment, trade or consumption [e.g. Cheng and Chiu (2018) for business cycles, Caldara and Iacoviello (2022) for growth and total factor productivity]. However, Egger and Gassebner (2015) find that international terrorism has only a moderate effect on bilateral and multilateral trade and income. Gaibulloev and Sandler (2019) show that terrorism has relatively trivial impacts on the whole economy, while the tourism and investment sectors experience more adverse but ultimately rather transient effects.

Regarding methodology, most of the literature on the relationship between GPRs and financial markets employs linear models. To overcome the weaknesses of linear models, though, some recent studies have used non-linear models. For instance, Kösedagli and Önder (2021) apply spatial modelling to examine the drivers of financial instability in emerging economies, finding that GPRs have a significant impact. In addition, Balcilar et al. (2018) use quantile regression to explore the role of GPRs in stock market dynamics in the BRICS countries. However, they do not base their analysis on panel data, which may provide more information than a time series approach (for a single cross-section) in modelling financial dynamics (Hsiao, 2007).

There are several nontrivial gaps in the empirical literature: the quantification of GPRs and FS, the estimation methods, and the extent of coverage. To fill these gaps, we begin by utilizing the GPR index computed by Caldara and Iacoviello (2022) because of its clear advantages in consistently quantifying GPRs across countries at a monthly frequency. Second, we compute the FS index based on the approach of Balakrishnan et al. (2011), which has been extended by Park and Mercado (2014) and is currently applied by the Asian Development Bank (ADB, 2021). This index not only covers a wide range of the subsectors in financial markets, but can also be extended to many emerging economies for a long time horizon at a monthly frequency. Third, for our estimation method, we use quantile regression analysis. While this method offers a high level of flexibility in modeling financial time series, it has scarcely been used in FS research. Finally, by dividing the overall financial sector into different subsectors (stock exchange, bond market, foreign exchange market, and banking sector), we can determine the implications of GPRs for these core parts of the financial system in greater detail; moreover, Saisana and Tarantola (2002) and European Commission and OECD (2008) argue that using subindicators is a pragmatic solution for addressing some of the weaknesses of composite indicators, such as offering overly simplistic and generalised policy advice.

3 | MODEL AND DATA

We deploy two approaches—fixed-effects models and quantile regression. We start with the fixed-effects estimator to verify major findings in the relevant literature.

3.1 | Econometric model

We focus on the quantile regression method because it is well suited to modelling the complex GPRs–FS relationship. Indeed, it provides insights not only into average or mean-to-mean relationships, but also into the relationships at high and low extremes and all other components of the distribution. In our paper, quantile regression answers two questions: Does geopolitical uncertainty affect financial stress symmetrically? How do different GPRs affect FS at different quantiles, especially during extreme episodes? The expansion beyond simple mean analysis is particularly useful because the relationship between GPRs and financial markets can be very different depending on whether the market is experiencing a tranquil or a turbulent period. Furthermore, there are several other properties that make quantile regression useful for studying financial time series: it is robust to outliers, it does not require strict distributional assumptions, and it is robust to a rather heterogeneous error structure (Uribe & Guillen, 2020).

Several quantile regression estimators for panel data have recently been developed (see Machado and Silva (2019), Galvao and Kato (2017) for a short review). In this paper, we use the approach developed by Machado and Silva (2019): a quantile regression model with individual ('fixed') effects. Firpo et al. (2009) call the approach adopted by Machado and Silva (2019) 'conditional' quantile regression (CQR) to differentiate it from their own 'unconditional' quantile regression (UQR). The quantiles in CQR are not predefined (as in UQR) but, rather, are determined by the control variables. Compared to other 'conditional' quantile regression approaches in the literature, Machado and Silva (2019)'s approach has several advantages, including its simple computation, the way in which it allows fixed effects to impact the entire distributions, and its applicability to non-linear models with multiple endogenous variables (Machado & Silva, 2019). The general model in Machado and Silva (2019) is:

$$Y_{t,m} = \alpha_m + \beta X_{t,m} + (\theta_m + Z_{t,m}\gamma)U_{t,m}(m = 1, 2, \ldots N; t = 1, 2, \ldots T)$$

where $(\alpha, \beta, \theta, \gamma)$ denote unknown parameters, Z is a k-dimensional vector of the transformations of the components of X as the vector of exogenous independent variables, for element l, $Z_l = \underline{Z}_l(X)$ $(l = 1, 2, 3, \ldots k)$. Fixed-effects for country m are captured by (α_m, θ_m). We assume that $P[\theta_i + Z_{t,m}\gamma > 0] = 1$, both $X_{t,m}$ and $U_{t,m}$ are $i.i.d.$ across m and t, and $U_{t,m}$ is independent of $X_{t,m}$ with $E(U) = 0$ and $E(|U|) = 1$.

We want to estimate the conditional quantiles of a random variable Y whose distribution is conditional on a set of explanatory variables X, $Q_Y(\tau|X)$ as:

$$Q_Y(\tau|X) = (\alpha_m + \theta_m q(\tau)) + \beta X_{t,m} + Z_{t,m}\gamma q(\tau) \tag{1}$$

where the quantile– τ country fixed effect (distribution effect) being $\alpha_m(\tau) \equiv \alpha_m + \theta_m q(\tau)$. This effect might change over different quantiles– τ. With $Z = X$, Equation 1 turns into:

$$Q_Y(\tau|X) = (\alpha_m + \theta_m q(\tau)) + X_{t,m}(\beta + \gamma q(\tau)). \tag{2}$$

From this equation, we can obtain the coefficients of X $\beta(\tau, X) = \beta + \gamma q(\tau)$ and their marginal effects at different quantiles (for details see Machado & Silva, 2019). To estimate the quantile coefficients, Machado and Silva (2019) propose the quantiles-via-moments approach. Their simulation study shows that the bias decreased significantly if $n/T < 10$, which is clearly our case with monthly data of around 30 years.

Different from CQR, in UQR, the changes in the set of control variables do not lead to changes in the quantile ranks. Firpo et al. (2009) estimate the UQR coefficients based on the idea of (recentred) influence function (RIF). It should be noted that CQR and UQR are based on two different concepts, meaning that a direct comparison of the magnitude of coefficients between the two approaches should be done cautiously. For example, CQR shows whether GPRs increase within-group dispersion in cases where the 'group' includes the FS indices that have the same values of the explanatory variables (other than GPRs). By contrast, UQR examines whether GPRs will increase the overall dispersion of FS, as indicated by the disparity between different quantiles of the unconditional FS dispersion (see Firpo et al. (2009) and Borah and Basu (2013) for illustrative examples).

For the purposes of this paper, we prefer CQR over UQR because CQR has already been widely used in the literature, has a long history dating back to the 1970s with the seminal work of Koenker and Bassett Jr (1978), and is seen by many as the most reliable quantile method. While we acknowledge that UQR uses a sound methodology and has some advantages over CQR, such as its high relevance to policy-making processes (Borah & Basu, 2013), our analysis aims to detect the different reactions of financial stress over different quantiles, not merely the marginal effect of GPRs on financial stress, making CQR a perfect fit for our research purpose. Moreover, to avoid too strong a focus on methodological discussion, which is beyond the scope of this study, we employ CQR as our major method (but still use UQR to provide further insights).

3.2 | Data construction and description

Our sample comprises 17 major emerging economies: Argentina, Brazil, China, Colombia, Hong Kong, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Russia, Saudi Arabia, South Africa, Thailand, and Turkey. The selection of economies depends only on the availability of GPRs and FS data.

3.2.1 | GPRs

Caldara and Iacoviello (2022) provide data on emerging economies from 1985. Country-specific GPR indices are computed based on the number of articles related to GPRs divided by the total number of the published articles for each month since 1899 in three major newspapers: the *New York Times*, the *Chicago Tribune*, and the *Washington Post*. These articles should reflect geopolitical topics through their use of words related to war, terrorism, or military actors.

In quantifying GPRs, the media-based GPR index of Caldara and Iacoviello (2022) has some advantages over the index used by the International Crisis Behaviour database (ICB), which lists manually military-security crises (NguyenHuu, 2022). First, in comparison to the ICB, the GPR index can provide a more accurate picture of how investors perceive geopolitical instability because major newspapers are quickly updated and are closely related to investors' interests. Moreover, the frequency of words related to geopolitics might reflect the severity of the risks

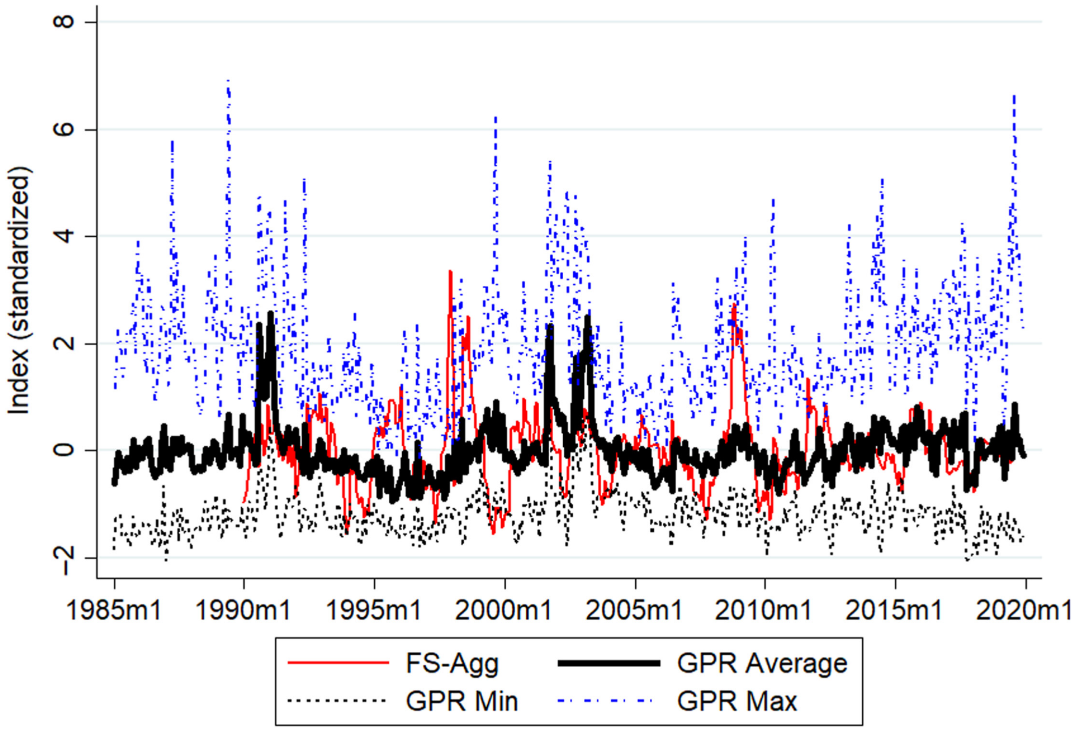

FIGURE 1 Geopolitical Risks Index: 1985–2019. [Colour figure can be viewed at wileyonlinelibrary.com]

more accurately than the number of actual conflicts recorded by historians, who fail to quantify the monetary or financial damage of conflicts. The newspaper-based index also covers a wider range of geopolitical threats than the ICB index because newspapers can cover complex issues, such as trade disputes and climate change, which are highly relevant to geopolitics but are not explicitly about actual military conflicts. Furthermore, at a high frequency, such as weekly or daily, conflicts can be recorded more accurately by GPR than by ICB because the start and the end dates of actual conflicts are not always clear.

Following Caldara and Iacoviello (2022), our variables are standardised for the convenience of interpretation and comparison. Figure 1 tracks the diverse dynamics of geopolitical vulnerability in emerging economies in connection to the collapse of the Soviet Union, the turn of the century, the global financial crisis, and the recent years the COVID-19 pandemic. These differences characterise the varied nature of emerging economies' responses to geopolitical situations.

3.2.2 | Aggregate and subsector FS indices

An index of financial conditions conveys important signals of the economy's health and is important to economic intervention policies and market dynamics (e.g. Afonso and Jalles (2020) for the responses of sovereign indebtedness to different financial conditions, IMF (2017–2023) for how global financial stability is evaluated through financial conditions barometer). In the literature, certain indices are used to quantify FS for individual economies. Duprey et al. (2017), for instance, construct the FS indices for EU countries, which are used by the European Central Bank to monitor the financial situation in Europe (European Central

Bank, 2021). The benchmark index, meanwhile, incorporates the stock price index, 10-year government bond yields, real effective exchange rates, banking sector stress, and the housing market. Extending this approach to emerging economies can be difficult, though, because of the limited availability of relevant data in the developing world. Another approach is that proposed by Koop and Korobilis (2014), which has been used by IMF to monitor financial situations in major regions of the world (IMF, 2017). Finally, to construct the FS index, Koop and Korobilis (2014) use a factor model for a wide range of financial variables. Their approach yields a comprehensive index rather than one that looks separately at subsegments of financial systems, which means that extending their approach to emerging economies over several decades might be challenging.

Based on the ideas from Balakrishnan et al. (2011), Park and Mercado (2014), and ADB (2021), our quantification of FS constructs a comparable and complete dataset for all major emerging economies, thus addressing the measurement challenges mentioned above. This approach is excellent for constructing the financial situations of different countries. The subcomponents of this index include banking sector β (*FS-Bank*), currencies market (*FS-EMPI*), debt market (*FS-Bond*), stock market return (*FS-Stk-rt*), and stock market volatility (*FS-Stk-vol*). Moreover, the index not only covers a wide range of subsectors in financial markets, but can also be extended to many emerging economies for a long time horizon at a monthly frequency. The construction of subsector FS indices is based on the following five components:

1. Banking sector β measures how risky the banking sector is in comparison to the market as a whole. It measures the relationship between the banking sector stock price index return (r) and the overall stock market price index return (m). A high β value may raise concerns regarding the banking industry risk.[1]

$$\beta = \frac{cov(r, m)}{var(m)} \tag{3}$$

2. EMPI measures the depreciation of the local currency with respect to the US dollar and the reduction in foreign exchange reserves. High EMPI index signals potential stress in the currencies market. With Δe and ΔRES being month-on-month percent changes in the foreign exchange rate and foreign exchange reserves, respectively, and σ and μ being the standard deviation and mean, respectively, we compute the following:

$$EMPI_{i,t} = \frac{(\Delta e_{i,t} - \mu_{i,\Delta e})}{\sigma_{i,\Delta e}} - \frac{(\Delta RES_{i,t} - \mu_{i,\Delta RES})}{\sigma_{i,\Delta RES}} \tag{4}$$

3. To proxy the financial stress in the bond market (*FS-Bond*), we employ yield differentials between long-term (10-year) local government bonds and US treasury bonds. In the literature,

[1]Some studies define a threshold of β to determine stress level, by converting β from continuous values to binary values (0/1) or 0/positive (e.g. Balakrishnan et al., 2011; Cardarelli et al., 2011). Following ADB (2021), we do not convert β into any new scale due to three reasons: (1) the determination of threshold or conversion method is arbitrary, (2) a common threshold is not appropriate for a large sample of very heterogenous emerging economies, (3) a conversion may distort the aggregate FS index. We acknowledge that choosing banking sector β as the single proxy for banking sector stress can lead to the over-simplification of banking stress index, other candidates can be the banking sector stock volatility, the slope of the yield curve or TED spread (Cardarelli et al., 2011). However it is hard to obtain data for such variables. For other subsector FS indices below, we use the similar approach as we do for banking FS index.

there are many ways to measure sovereign risks (e.g. Popescu & Turcu, 2017). We use the sovereign yield spreads in order to gain access to more available data. A large yield spread may reflect instability in the debt market.

4. Stock return (*Stk-rt*) is calculated as the difference between the current and previous 12-month stock price index in natural logarithms. Namely,

$$\mathrm{Stk{-}rt}_{i,t} = ln(Stock_{i,t}) - ln(Stock_{i,t-12}) \tag{5}$$

The stress of the stock market return is computed by multiplying the *Stk-rt* by minus one, so that higher FS in the stock market suggests a decrease in stock return. Drops in stock return indicate significant problems with the financial condition.

5. Stock volatility (*Stk-vol*) σ^2 is measured using a GARCH (1,1) process as follows:

$$\sigma^2 = \omega + \phi_1 \varepsilon_{t-1}^2 + \phi_2 \sigma_{t-1}^2 \tag{6}$$

where σ^2 and ε are the variance and error term in the return regression as an autoregressive process with 12 lags. Big swings in the stock market threaten financial stability.

Following ADB (2021) and Park and Mercado (2014), we construct the aggregate FS index using principal component analysis and sum up the first two components to represent the overall dynamics of financial conditions. Other methods for constructing a composite FS index have certain disadvantages: simple averaging is biased toward outliers and variance-equal weights might be arbitrary in its selection of weighting methods and often produces erratic and volatile patterns (Park & Mercado, 2014).

Figure 2 illustrates our aggregate FS indices over time. The most turbulent times for most emerging economies occurred around the time of the global financial crisis. Other stressful times coincided with crises at the regional or country level, such as the Asian financial crisis, the Russian default, the Brazil crisis of 1997–1998, the Turkish stock market crash, the outbreak of SARS, and various economic crises in Argentina in the early 2000s. In terms of subsector dynamics, stress levels across subsectors tend to differ and sometimes deviate from the overall market, especially during episodes of high instability. This prompts us to scrutinise the GPR-FS relationship not only at the aggregate but also at subsector levels.

For model specification, in addition to GPRs index, we use FS indices of other emerging economies and the G7 countries (to proxy transmission effects), individual country, and global control variables following Balakrishnan et al. (2011), Park and Mercado (2014), and Das et al. (2019). Individual economy control variables include annual GDP growth, fiscal account measured by general government net lending/borrowing as a percentage of GDP, the current account balance as a percentage of GDP, the Chinn-Ito Financial Openness Index, and trade openness as the percentage of trade in GDP. Global control variables include monthly commodity price changes, the global economic activity index, and the LIBOR 3-month rate. All economy-specific control variables are recorded on a yearly basis.[2]

[2]Park and Mercado (2014) interpolates yearly data to create monthly data. In our analysis, the main interest is not to investigate the determinants of FS, moreover, interpolated data is not real data, thus we keep the economy-specific control variables at their original frequency.

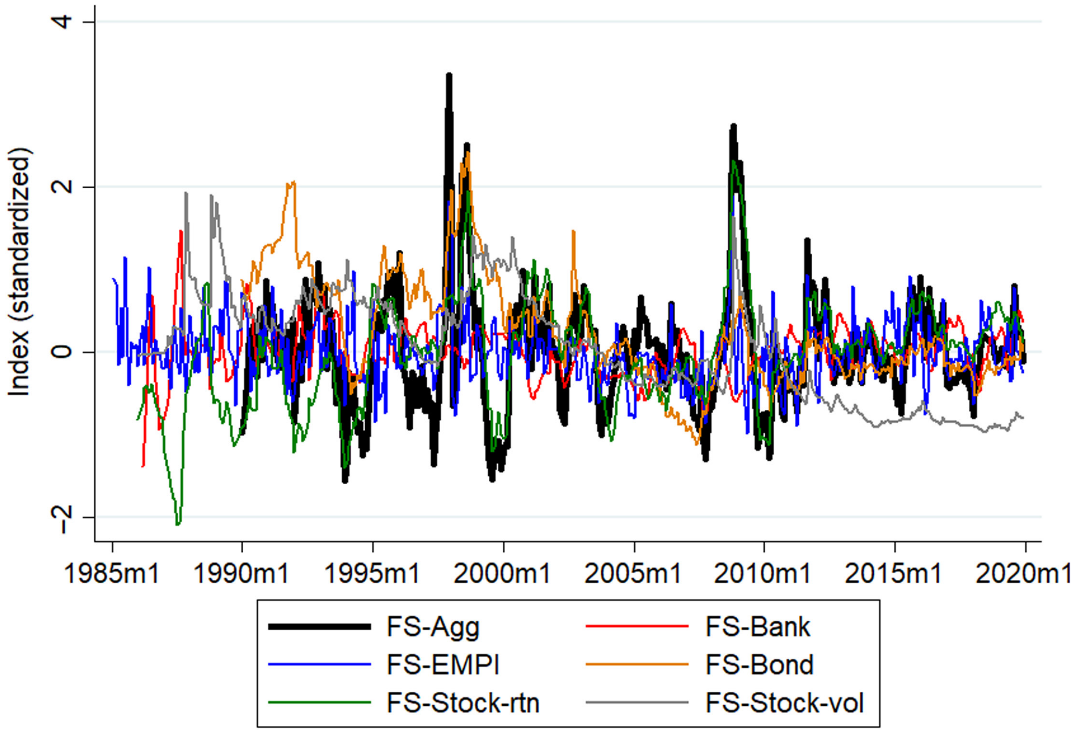

FIGURE 2 Aggregate Financial Stress Index: 1985–2019. [Colour figure can be viewed at wileyonlinelibrary.com]

As a common practice in the literature, some control variables are transformed using first differencing due to the potential presence of a unit root. The concern regarding reverse-causality or endogeneity of GPRs in FS regression is largely mitigated. This is because GPRs, which are highly relevant to conflict-fuelling events, are almost exogenous to financial conditions. Table 1 reports the descriptive statistics and sources of our data.[3]

4 | EMPIRICAL RESULTS

This section presents our findings on the unfavourable and diverse effects of GPRs on financial conditions in emerging and advanced economies.[4]

[3]For global variables, which are the same for all countries (i.e. single time series), we apply univariate unit root test, while we use panel unit root test for country-specific variables. We test for stationarity of our time series by using Dickey-Fuller for univariate data and Pesaran's panel unit root test which allows for cross-sectional dependence in panel data. The null hypotheses of the unit root are rejected at a 5% significance level for all tests in our analysis.

[4]The tables here report analytical standard errors. We also calculate bootstrapped standard errors clustered at the economy level (100 replications; in the spirit of Machado and Silva (2019) and Firpo et al. (2009)), which produce qualitatively similar results in major models. It should be noted that the clustered standard errors, which are robust to heteroskedasticity and within-cluster error correlation, might lead to the asymptotic tests to overreject, especially when the number of clusters is not large (Cameron et al., 2008). In our case, there are only 17 clusters (economies), therefore the interpretation based on clustered standard errors might be too conservative.

TABLE 1 Data description.

Variable	Obs.	Mean	Std.	Min	Max	Fre.	Sources
FS-Agg.	4002	0	1	–4.53	8.96	M	Datastream
FS-Bank	5536	0	1	–4.45	6.28	M	Datastream
FS-EMPI	6941	0	1	–12.4	13.2	M	Datastream
FS-Bond	4122	0	1	–3.07	5.4	M	Datastream
FS-Stk-rt	6336	0	1	–5.19	3.91	M	Datastream
FS-Stk-vol	6336	0	1	–1.63	10.20	M	Datastream
GPRs	7140	0	1	–2.07	6.94	M	CI
Glo.Com.Pr	7140	0.34	3.40	–15.4	17.0	M	WB
Glo.Eco.Act.	7140	0.04	0.38	–2.17	1.14	M	DFED
Glo.LIBOR	6919	–0.02	0.25	–1.59	1.24	M	FRED
GDP-gr	7068	4.29	4.25	–14.5	17	Y	WB
Fiscal-acc.	6792	–1.93	4.16	–17.2	29.8	Y	WB
Balance-acc.	7056	0.70	5.39	–20.8	27.4	Y	WB
Fin.Open.	6804	0.004	0.09	–0.59	0.59	Y	Chin/Ito
Trade.Open.	6888	0.72	8.37	–41.8	84.3	Y	WB

Note: Fre.: Frequency of data, monthly (M) or yearly (Y). CI: Caldara and Iacoviello (2022).
FRED: FED of St. Louis, DFED: Dallas FED, Kilian (2009), Chin/Ito: Chinn and Ito (2006), WB: World Bank.

TABLE 2 GPR and aggregate FS in emerging economies: fixed-effects regression (FE).

	(1)	(2)	(3)	(4)	(5)
Model	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**
GPRs	0.085*** (0.016)	0.044*** (0.014)	0.036** (0.014)	0.042*** (0.012)	0.033*** (0.011)
FS-Agg.eme.		0.400*** (0.058)	0.345*** (0.027)	0.402*** (0.058)	0.347*** (0.054)
FS-Agg.adv.		0.162*** (0.038)	0.099*** (0.033)	0.161*** (0.037)	0.099*** (0.033)
Glo.Com.Pr.			0.005 (0.005)		0.005 (0.004)
Glo.Eco.Act.			–0.550*** (0.155)		–0.547*** (0.156)
Glo.LIBOR			–0.194* (0.100)		–0.195* (0.100)
GDP-gr				–0.028** (0.01)	–0.028*** (0.009)
Fiscal-acc				–0.005 (0.006)	–0.005 (0.006)
Balance-acc				–0.016*** (0.004)	–0.015*** (0.004)
Fin.Open.				–0.186 (0.325)	0.170 (0.324)
Trade.Open.				0.006** (0.002)	0.007** (0.003)
Year	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Obs.	4002	4002	4002	4002	4002
R-squared	0.128	0.333	0.347	0.335	0.349
VIFs	5.17	5.05	4.99	4.95	4.90

Note: Robust standard errors in round brackets. VIFs: variance inflation factors.
Abbreviation: VIFs, variance inflation factors.
*, ** and ***: significance at 10%, 5% and 1%, respectively.

4.1 | GPRs and FS in emerging economies: fixed-effects model

Table 2 shows that GPRs matter greatly to FS in emerging economies. One standard deviation increase in GPRs causes a standard deviation increase of between 0.033 (model 5) and 0.085 (model 1) in the composite FS index. The impacts are statistically significant over different specifications with different sets of control variables. The magnitude of such effects is equal to one-third of the contagion caused by the FS in advanced economies and slightly higher than the impacts of a 1% decline in GDP growth. Our models explain approximately 34% of the dynamics of the financial situations of emerging economies, which is comparable to previous studies, such as Park and Mercado (2014). Regarding the control variables, Table 2 qualitatively confirms some major findings shown in Park and Mercado (2014) and Balakrishnan et al. (2011). The significant effects of contagion from other emerging economies, global economic activity, GDP growth, and trade openness are as expected.

Table 3 highlights the differing impacts of GPRs on different segments of the financial industry. It shows that only some effects of geopolitical turbulence can be seen in the currencies market. The stock markets, both return and volatility measurements, the banking sector, and the bond market encounter statistically insignificant effects (except for the simplest model specification for stock returns). These results suggest that the OLS approach may be insufficient to examine the subtle and complicated relations between financial time series. To address this, we use quantile regression analysis in the following part to explore further the implications of GPRs on financial conditions.

4.2 | GPRs and FS in emerging economies: quantile regression

As can be seen in Table 2, both country-specific and global control variables contribute slightly to the explanatory power of the model (R^2 remains almost unchanged). Moreover, our analysis does not set out to comprehensively investigate the determinants of FS. Therefore, to keep the model parsimonious without compromising its explanatory power and while also avoiding the mixed frequency (monthly/yearly) of control variables, in the following models we keep only contagious control variables (FS in emerging and advanced economies).[5]

Table 4 shows that GPRs do not have statistically significant effects on the FS index at the lowest quantile. Rather, the effects are considerably stronger and statistically significant at the middle and higher quantiles. This means that GPRs might put more pressure on the financial market, especially when the economy already suffers certain levels of stress. In contrast, when the financial conditions are favourable, GPRs have only trivial impacts. In other words, GPRs cannot trigger FS, but they can escalate an already worsening situation.

Table 4 reveals that the impacts of geopolitical uncertainties are diverse across different segments of the financial market and across quantiles within a specific segment. First, the banking sector stress is intensified by heightened GPRs, but only at the lowest or middle quantiles. At low quantiles, the greater the GPRs are, the higher the FS indices become. The impacts of geopolitical problems become insignificant when the banking industry becomes more unstable. This might be because when the banking sector is already under some stress,

[5]We also conducted regression analyses with different set of control variables and the results are qualitatively similar and can be provided upon request.

TABLE 3 GPRs and FS in subsectors in emerging economies: fixed-effects regression (FE).

Model	(1)	(2)	(3)	(4)	(5)
Controls	No	Yes (a)	Yes (a,b)	Yes (a,c)	Yes (a,b,c)
	FS-Bank	FS-Bank	FS-Bank	FS-Bank	FS-Bank
GPRs	0.021 (0.029)	0.022 (0.028)	0.030 (0.029)	0.023 (0.029)	0.030 (0.030)
R^2	0.037	0.050	0.054	0.052	0.057
	FS-EMPI	FS-EMPI	FS-EMPI	FS-EMPI	FS-EMPI
GPRs	0.032** (0.014)	0.031* (0.015)	0.031** (0.014)	0.021* (0.011)	0.021* (0.011)
R^2	0.028	0.084	0.092	0.105	0.109
	FS-Bond	FS-Bond	FS-Bond	FS-Bond	FS-Bond
GPRs	0.101 (0.059)	0.099 (0.059)	0.092 (0.058)	0.076 (0.053)	0.069 (0.053)
R^2	0.268	0.278	0.282	0.319	0.324
	FS-Stk-rt	FS-Stk-rt	FS-Stk-rt	FS-Stk-rt	FS-Stk-rt
GPRs	0.067** (0.023)	0.022 (0.021)	0.021 (0.022)	0.026 (0.023)	0.025 (0.023)
R^2	0.271	0.385	0.388	0.421	0.423
	FS-Stk-vol	FS-Stk-vol	FS-Stk-vol	FS-Stk-vol	FS-Stk-vol
GPRs	−0.006 (0.024)	−0.020 (0.023)	−0.023 (0.023)	−0.027 (0.025)	−0.029 (0.025)
R^2	0.378	0.404	0.404	0.418	0.419

Note: a: FS-Agg controls, b: Global and c: Country-specific controls, country & year effects included.
*, ** and ***: significance at 10%, 5% and 1%, respectively. Robust standard errors are in round brackets.

other more direct drivers of that stress, such as the macroeconomic situation, monetary policies, intervention policies of the governments, and banks' own 'defense' strategies, might play a more significant role than geopolitical issues. For example, Caplain et al. (2017) observe that the banking sector maintains a holistic approach to managing risk, meaning that it tends to overreact during geopolitical unpredictability. Our findings on the significant impacts of GPRs on FS at low quantiles should be interpreted cautiously because a small increase in banking sector β, especially at low quantiles, does not necessarily indicate a significant concern regarding systematic risk[6].

In contrast, the effects of GPRs on foreign exchange markets are seen only at medium and high quantiles. Furthermore, the magnitude of these impacts is remarkably stronger than in the overall financial sector. For example, within the 90th quantile, one standard deviation increase in GPRs might lead to a standard deviation increase of 0.088 in the FS index of the currencies market. This value is significantly higher than the value of 0.052 found in the overall financial market. In other words, geopolitical problems have major implications for the instability of emerging foreign exchange rate markets, especially when these markets are already in medium or high stress. These findings are fairly similar to those of Petrov et al. (2019), who show that the currency markets in India, Israel, South Korea, and Turkey have strong and rapid reactions to geopolitical events. Our regression outcome is also consistent with Salisu

[6]It is often considered that banking sector β smaller than 1 is relatively safe. Therefore, if GPRs increase β, but β value is still under 1, then the concern is not serious.

TABLE 4 GPRs and FS in emerging economies: conditional quantile regression (CQR).

	Null hypothesis: Coeff. = 0					Test Coeff. Equal.	
	Q1	Q3	Q5	Q7	Q9	Q1 = Q5	Q1 = Q9
Dep.Var.	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**		
GPRs	0.037 [0.025]	0.041 [0.016]**	0.044 [0.014]***	0.047 [0.017]***	0.052 [0.028]*	0.31 0.58	0.35 0.55
Dep.Var.	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**		
GPRs	0.049 [0.024]**	0.035 [0.016]**	0.025 [0.014]*	0.013 [0.018]	–0.007 [0.030]	2.96 0.086	4.15 0.042
Dep.Var.	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**		
GPRs	–0.022 [0.023]	0.01 [0.015]	0.029 [0.014]**	0.049 [0.016]***	0.088 [0.027]***	10.7 0.001	16.81 0.000
Dep.Var.	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**		
GPRs	0.054 [0.028]*	0.076 [0.019]***	0.095 [0.017]***	0.117 [0.021]***	0.147 [0.035]***	11.27 0.001	11.31 0.001
Dep.Var.	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**		
GPRs	0.036 [0.941]	0.028 [0.594]	0.022 [0.349]	0.016 [0.118]	0.008 [0.205]	1.88 0.170	1.76 0.185
Dep.Var.	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**		
GPRs	–0.006 [0.018]	–0.012 [0.012]	–0.018 [0.015]	–0.026 [0.026]	–0.038 [0.048]	2.91 0.088	3.1 0.078

*, ** and ***: significance at 10%, 5% and 1%, respectively, analytical standard errors in square brackets.

Bootstrapping equality test: test statistics on the left, *p*-value on the right.

et al. (2021), who find there to be varied vulnerability levels of BRICS exchange markets under high pressure from GPRs.

The significant impacts of GPRs on exchange rate markets in emerging economies can be explained by several channels. For example, GPRs damage international trade (Glick & Taylor, 2010), and this poses a high risk to the stability of exchange rates and international reserves. Furthermore, GPRs trigger flight-to-safety capital flows during geopolitical turmoil. Caldara and Iacoviello (2022) find that an increase of one standard deviation in the GPR index reduces capital flows in emerging economies by 0.23 percentage points, yet it increases capital flows in advanced economies by 1 percentage point.

In a pattern similar to that of the currencies market, GPRs affect bond markets across all quantiles, with higher quantiles seeing more measurable effects. Bond markets are highly vulnerable to geopolitical uncertainties when these markets are already under stress. The consequences of GPRs in this segment are twice as high as in the overall financial industry. As Presbitero et al. (2016) argue, FS in bond markets (measured by bond spread) might be more severe when countries are weaker in terms of trade, fiscal positions, growth, and government effectiveness. Our findings indicate that GPRs might raise considerable concerns regarding the capacity of governments in emerging markets to manage risks. Given that there is strong evidence of the contagion of sovereign risks, both in the eurozone and across the globe [see Badarau et al. (2014) for the Eurozone example and Beirne and Fratzscher (2013) for the global evidence], the significant effects of GPRs on the bond market in one country might trigger larger impacts in other countries, especially when the fundamentals are deteriorating during crises and countries are closely connected.

In marked contrast to other segments of the financial system, stock markets, in terms of both return and volatility measurements, are sufficiently strong to withstand geopolitical turbulence. Table 4 shows that GPRs have negligible consequences on FS in stock markets. This confirms the heterogeneous reactions of stock markets in emerging economies to geopolitical uncertainties. Our evidence of a loose correlation between stock market performance and GPRs is supported by Petrov et al. (2019), who conduct a simple descriptive analysis of the link between GPRs and the MSCI World index. Using quantile regression, Balcilar et al. (2018) also show mixed evidence regarding the consequences of GPRs in BRICS countries.

Our findings on stock markets stand in contrast to those of Arin et al. (2008). Their results demonstrate that terror has a significant and negative impact on stock market returns and volatility, and their magnitudes are greater in emerging markets than in advanced markets. However, the event study by Arin et al. (2008) focuses on only six countries and considers only major terrorist events. Like Arin et al. (2008), Petrov et al. (2019) demonstrate that major geopolitical events have some negative effects on stock returns in four emerging markets. The profound impacts of GPRs on stock markets are found only in the studies that use subjectively selected samples of geopolitical events (mostly large-scale terrorist events, such as in Wade & Lauro, 2019), or specific countries (mostly those with high vulnerability or great exposure to terrorism), although the concern regarding the selection bias of event studies is high in these cases.

We use bootstrapping to test the equality of the coefficients across quantiles in the last column of Table 4. Looking at this, we can see that there is a statistically significant difference between coefficients across quantiles for subsector FS but not for aggregate FS. However, this equality test result for aggregate FS should be interpreted cautiously. The CQR standard errors reported in Table 4 (columns Q1–Q9) indicate that the null hypothesis (the GPRs' coefficient is equal to zero)

TABLE 5 GPRs and FS in emerging economies: unconditional quantile regression (UQR).

	Null hypothesis: Coeff. = 0					Test Coeff. Equal.	
	Q1	Q3	Q5	Q7	Q9	Q1 = Q5	Q1 = Q9
Dep.Var.	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**		
GPRs	0.047 [0.025]*	0.031 [0.017]*	0.033 [0.015]**	0.032 [0.018]*	0.060 [0.031]*	0.4 0.529	0.09 0.760
Dep.Var.	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**		
GPRs	0.047 [0.022]**	0.037 [0.014]***	0.001 [0.014]	0.034 [0.018]*	0.004 [0.028]	4.04 0.044	1.83 0.177
Dep.Var.	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**		
GPRs	0.013 [0.020]	0.005 [0.010]	0.022 [0.008]***	0.044 [0.011]***	0.087 [0.023]***	0.25 0.616	7.11 0.008
Dep.Var.	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**		
GPRs	0.042 [0.019]**	0.070 [0.014]***	0.101 [0.016]***	0.156 [0.028]***	0.074 [0.028]***	7.21 0.007	1.19 0.275
Dep.Var.	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**		
GPRs	–0.006 [0.026]	0.006 [0.015]	0.044 [0.011]***	0.034 [0.011]***	0.012 [0.023]	3.63 0.057	0.34 0.560
Dep.Var.	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**		
GPRs	0.002 [0.009]	0.003 [0.007]	–0.003 [0.008]	–0.015 [0.016]	–0.064 [0.030]**	0.15 0.698	6.01 0.014

*, ** and ***: significance at 10%, 5% and 1%, respectively, analytical standard errors in square brackets.

Bootstrapping equality test: test statistics on the left, *p*-value on the right.

cannot be rejected when FS is at low quantiles, but can be rejected comfortably when the aggregate FS is at high quantiles (at 5% significance level).[7]

As shown in Table 5, the major findings from UQR qualitatively verify our previous findings using CQR. Namely, there is strong evidence that GPRs affect FS at middle and high quantiles. The effects are strong in foreign exchange markets, especially at high quantiles. Similarly, the banking sector and the bond market reflect significant influences of GPRs at low and high quantiles, respectively. However, the UQR results show that GPRs have significant impacts on stock returns and volatility, albeit at only certain quantiles.

4.3 | GPRs and FS in G7 economies

Table 6 presents the results for advanced economies (G7). Because geopolitical events occur mostly in emerging economies, to measure the impacts of GPRs in advanced economies, we use the global GPRs in all models. Just as they do for emerging economies, GPRs have negative implications for the financial situation in advanced economies. One unit increase in the standard deviation of GPRs leads to a standard deviation increase of around 0.11 in the FS index.

One crucial difference between advanced economies and emerging economies is that the impacts of GPRs in advanced economies are similar across quantiles. This indicates that geopolitical disorders from emerging economies might affect financial situations in advanced economies in a rather homogeneous pattern.

There are several potential explanations for the differences between emerging and advanced economies in terms of the magnitude of the impacts they have across quantiles. First, the GPR index used in our analysis focuses more on worldwide or more western-oriented risks than on regional or country-specific risks because it only incorporates English-speaking media outlets. Thus, although the examined newspapers are popular and have a wide coverage, they might fail to take into account the important country-specific context of geopolitical events, capture only general information due to limited space for international news, report news relatively late, or ignore the long-time development of events. This is very different to domestic newspapers, which provide more details on the events as well as the relevant context. Several studies have been conducted that use national media sources rather than international ones to investigate the impacts of GPRs on financial market, including those by Jung et al. (2021) and Dibooglu and Cevik (2016). Second, the differing reactions of emerging and advanced economies might be caused by the differences in their economic and social nature. Indeed, readers of newspapers in emerging economies and advanced economies have different backgrounds and country-specific knowledge. Namely, the followers of English newspapers in advanced economies might have a poorer understanding of geopolitical situations in a typical emerging economy than the local people do. The previous literature on the impacts of GPRs in event studies or

[7]The conclusion drawn from our analysis is based on the null hypothesis of GPRs' coefficient equal to zero. The increase of GPRs' coefficients from 0.037 to 0.047 (Q1 and Q7, respectively, Table 4) indicates only a higher within-group dispersion but presents no clue on between-group dispersion (the overall FS dispersion between different quantiles of the unconditional FS dispersion). We also conducted another test of equality between coefficients of different quantiles. Following Clogg et al. (1995), we calculated Z-statistics ($\widehat{Z} = \frac{\beta_1 - \beta_2}{\sqrt{(SE\beta_1)^2 + (SE\beta_2)^2}}$, where β and SE are coefficient and standard errors, respectively) for the GPRs' coefficients of Q9 and Q1 and find the significant differences in the FS-EMPI and FS-Bond, but not in the FS-Agg and FS-Bank regressions. We prefer bootstrapping test over Z-score because using Z-scores may require some independence assumption of samples.

TABLE 6 GPRs and FS in G7 economies: conditional quantile regression (CQR).

	Null hypothesis: Coeff. = 0					**Test Coeff. Equal.**	
	Q1	**Q3**	**Q5**	**Q7**	**Q9**	**Q1 = Q5**	**Q1 = Q9**
Dep.Var.	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**	**FS-Agg.**		
GPRs-Global	0.107 [0.042]**	0.112 [0.027]***	0.115 [0.024]***	0.120 [0.031]***	0.126 [0.051]***	0.25 0.615	0.14 0.711
Dep.Var.	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**	**FS-Bank**		
GPRs-Global	0.059 [0.031]*	0.045 [0.021]**	0.035 [0.018]*	0.023 [0.023]	0.002 [0.041]	2 0.157	2.24 0.135
Dep.Var.	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**	**FS-EMPI**		
GPRs-Global	0.021 [0.083]	0.009 [0.053]	0.002 [0.053]	–0.005 [0.068]	–0.016 [0.111]	1.37 0.243	1.99 0.158
Dep.Var.	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**	**FS-Bond**		
GPRs-Global	0.013 [0.051]	0.009 [0.035]	0.006 [0.032]	0.002 [0.043]	–0.002 [0.068]	0.76 0.385	0.72 0.398
Dep.Var.	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**	**FS-Stk-rt**		
GPRs-Global	0.013 [0.032]	0.045 [0.021]**	0.067 [0.017]***	0.089 [0.020]***	0.122 [0.033]***	13.72 0.000	15.11 0.000
Dep.Var.	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**	**FS-Stk-vol**		
GPRs-Global	0.012 [0.052]	0.032 [0.038]	0.049 [0.030]*	0.069 [0.029]**	0.105 [0.050]**	2.43 0.119	2.88 0.090

*, ** and ***: significance at 10%, 5% and 1%, respectively, analytical standard errors in square brackets.

Bootstrapping equality test: test statistics on the left, *p*-value on the right.

single-country analyses (see e.g. Balcilar et al., 2018) shows that the impacts are strong only in some specific countries and after some specific events. The impacts in our sample of emerging countries may be less pronounced or visible than in our sample of advanced countries because our sample includes many emerging countries with very diverse development levels, economic structures, or varied resilience levels to shocks and crises. In contrast, because advanced economies are highly connected with mature financial markets and have similar economic and social structures, the impacts of GPRs on advanced countries might be more homogeneous than in emerging economies.

In regard to subsectors, there is an even greater difference between advanced and emerging economies. The stock markets in advanced economies see adverse impacts of GPRs on both market return and market volatility. Furthermore, significant and destructive effects are found in high-stress episodes for both measurements of stress. One possible explanation for these impacts may be that the stock markets are internationally connected and emerging markets play a significant role in advanced economies. Therefore, the spillover effect of shocks from the outside world, especially from emerging economies, is sizeable. This result is consistent with Chesney et al. (2011), who find that 77 large-scale terrorist events (around 80% of which occurred in emerging economies) have had significant impacts on advanced economies.

In contrast, other sections of the financial system, such as foreign exchange markets, bond markets, and banking sectors, are almost unaffected by geopolitical uncertainties in emerging economies. This apparent lack of correlation can be explained by the way the stress indices of these subsectors are aggregated. The *EMPI* is constructed by using foreign exchange rates and reserves, and the FS index in debt markets measures government bond spreads. All these components are largely driven by domestic factors, with government policies playing an essential role. In other words, the subsectors of all advanced economies are more reliant on the subsectors of the US economy rather than on other emerging economies' subsectors. The banking sectors of advanced economies suffer only some disruptive impacts of GPRs at low quantiles.

5 | CONCLUSIONS

Our paper finds that GPRs play a prominent role in shaping the financial conditions of emerging economies. Our main results show that, in emerging economies, foreign exchange markets and, to a lesser degree, the banking and debt sectors might be among the hardest-hit areas. Our quantile analyses establish that the magnitude of the impacts is largely driven by the stress level of the corresponding markets. These profound effects are not observed in stock markets, though, which tend to be relatively robust to external disturbances from geopolitical events. This is in stark contrast to advanced economies, where GPRs have major impacts that are concentrated mostly on the stock markets.

These findings could prove useful for both political and business decision-makers. For instance, based on our results, we recommend that appropriate reaction plans be made to prepare for blooming geopolitical uncertainties, especially when the financial markets reveal certain stress signals. Moreover, reaction plans should take into account different policies for different subsectors because GPRs do not affect all subsectors equally. Investors, meanwhile, should consider the fragility of the relevant asset markets when they build up or adjust their portfolios.

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DATA AVAILABILITY STATEMENT

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

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