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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 between 1985 and 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. In contrast, 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) economies, have witnessed detrimental consequences of GPRs on their stock markets but negligible effects on other parts of their financial systems.

Keywords: geopolitical risks; financial stress; emerging economies; stock market; banking sector; foreign exchange market; debt market.

JEL classification: F36, F62, G15

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1. Introduction

Ushering in an era of great uncertainty, geopolitical risks (GPRs) are among the most important dangers to the global economy. They are considered major threats to the stability of the world on many fronts, including economics, politics, and technology (The Economist, 2021). These risks can emerge from a wide range of events, both local and global: from military interventions, terrorist attacks, trade disputes, and political gridlock, to climate change, cyberattacks, and the COVID-19 pandemic (Blackrock Investment Institute, 2021). Given the increasingly integrated 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 how much the financial stress (FS) in emerging economies can be attributed to geopolitical uncertainties.

In his speech on June 30, 2016, Mark Carney, the Governor of the Bank of England, argues that GPRs are one of three components of "the uncertainty trinity", which is responsible for "a form of economic post-traumatic stress disorder amongst households and businesses, as well as in financial markets" (Carney, Mark, 2016, p.5). He further shows that GPRs have significant repercussions on risk awareness and economic decisions of individuals, and they clearly negate the output. At the "Challenges for Monetary Policy" symposium in Kansas City, Jerome H. Powell, the 16th Chair of Federal Reserve, also lists GPRs, which cause strong reaction of financial markets, as one of the major challenges to the conduct of monetary policies in the US (Powell, 2019). Viewing a broader landscape, the International Monetary Fund and the World Bank have constantly put geopolitical tensions as an important challenge and major source of instability around the globe (see e.g. IMF 2021a, IMF 2021b, World Bank 2021).

Monitoring the developments of GPRs become an important part of the business agendas of many banks, asset management companies, and consultancy firms, among others, McKinsey (2016), JP Morgan (2019), Blackrock Investment Institute (2021), The Economist (2021), BCA Research (2021), and IHS Markit (2021), to name a few. For example, Blackrock Investment Institute (2021) uses its own dashboard to trace the weekly development of global GPRs. The Economist (2021) monitors major global risks with special attention to geopolitical problems in its coverage. BCA Research (2021) and IHS Markit (2021) provide regular reports for the business world to track worldwide geopolitical uncertainties and their business implications. The geopolitical risk barometer of Caldara & Iacoviello (2017) has been widely used in the business world (Petrov et al., 2019). Wade & Lauro (2019) emphasize that GPRs are often considered as the greatest tail risk for investors.

There are several efforts in the empirical literature to examine the influences of GPRs on some separate parts of the financial environment in emerging economies. The studies identify three major issues. First, how to measure GPRs and FS properly and systematically in emerging economies at a high frequency? Second, how to account for the typical features of long financial time series in examining the impacts? Finally, how to provide not only a comprehensive picture of the impacts on the whole financial system but also on the subsectors of the financial system or on the mechanisms of these impacts?

Using monthly data from 1985 to 2019 for 17 major emerging economies, we attempt to address all three issues. First, we use comprehensive and comparable indicators of GPRs, aggregate and subsector FS across all major emerging economies. Our data have clear advantages in terms of coverage, frequency, and consistency. Second, in terms of method, we apply the panel quantile regression method recently proposed by Machado & Silva (2019). In general, the quantile regression method is more robust than ordinary least squares estimation when the series include outliers and have non-normal distributions, and this is the case for FS indices. Third, by dividing the overall financial sector into different segments: stock market, debt market, foreign exchange market, and banking industry, we can determine which parts of the financial markets are more vulnerable to GPRs. This detailed analysis might enable a better understanding of the impacts of geopolitical turbulence. Fourth, we compare the implications of GPRs, which occur mostly in the emerging world, on G7 countries[1] to evaluate the contagion of geopolitical threats. To our knowledge, a comparison between emerging and advanced economies on

[1] Canada, France, Germany, Italy, Japan, the UK and the US

the consequences of GPRs is rare in the literature.

Our analysis provides important insights for policymakers and investors to react better to geopolitical threats, which are occurring with increasing frequency. We point out that GPRs have pronounced impacts on a global scale. In general, heightened GPRs aggravate the stress in the financial system. The impacts are diverse, depending on the subsectors affected, the severity of financial stress, and the country groups being examined. These findings are of high relevance for monitoring global financial markets, managing and preparing for macro risks, and making investment decisions in both normal and turbulent times. This has become more important since geopolitical uncertainties are more complex, interregional, contagious, and increasingly unpredictable.

Our paper is structured into five parts. Following this introduction, Sections 2 briefly reviews the theoretical and empirical literature on GPRs, FS, and how they are connected. Sections 3 and 4 present our data, model and estimation results. We conclude our paper in the last section.

2. Literature Review

2.1. Theoretical Framework

Our research topic pertains to the literature on the consequences of terrorist attacks, wars, conflicts (Eckstein & Tsiddon, 2004), rare disasters (Barro, 2006), and uncertainty shocks (Bloom, 2009). Such geopolitical turbulence can directly or indirectly affect the financial situation in emerging economies through macro- and micro-channels (for a review, see Lenain et al. 2002, Blomberg et al. 2004, Frey et al. 2007, Ferguson 2008, Sandler & Enders 2008, Gaibulloev & Sandler 2019, and Wang & Young 2020, among others). At the macro level, GPRs might enormously depreciate the human and capital resources of nations in the short and long term. Defense spending and the cost of war increase in parallel with conflicts and other security risks (Eckstein & Tsiddon, 2004). Furthermore, both ongoing and potential conflicts might threaten the stability of countries, damaging foreign capital and trade flows and breaking the connection to the outside world (Caldara & Iacoviello 2017, Sandler & Enders 2008, Petrov et al. 2019, Glick & Taylor 2010). At the micro level, by causing uncertainties, GPRs might distort individual economic behavior, undermine consumer confidence, and drive down sentiments, leading to poor decisions on investments, consumption, and savings. GPRs also have damaging effects on human well-being, triggered by insecurity and fears (Lenain et al. 2002, Frey et al. 2007, Petrov et al. 2019).

A widely cited theoretical framework for the impact of terror on the well-being of individuals and the macroeconomy is presented by Eckstein & Tsiddon (2004). Their approach is an extension of the Blanchard–Yaari model (Yaari 1965, Blanchard 1985, Blanchard et al. 1989), which assumes that the individuals live in a closed economy with an infinite horizon. Eckstein & 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 cannot offset the damages yielded by terror. As a result, terror reduces investment, output, and consumption. It depreciates individual health and destroys human capital.

Another relevant theoretical framework is the rare macroeconomic disasters model developed by Barro (2006) to resolve the asset-pricing puzzles. Wars are included among the rare disasters that rarely occur but can cause tremendous harm to the macroeconomy (Barro & Ursúa, 2008). The huge drops in consumption that accompany such disasters—even though they are rare—help to explain the dynamics of many financial asset prices and risk premiums over time, such as stock, real estate, government bills, exchange rates, and options (see Tsai & Wachter 2015, Nakamura et al. 2013, Barro & Liao 2021 for details).

Throughout the history, geopolitical instability has been a source of uncertainty shocks. Bloom (2009) constructs a model to simulate a macroeconomic uncertainty shock, which results in a huge and fast drop in consumption followed by a quick recovery in output and employment. Bloom (2009) argues that such uncertainty shocks could force firms to cut off their production temporarily. But the recoveries would be expected in the medium-term because of the increased volatility caused by the shock. This implies that GPRs might have strong but short-term impacts on the overall economy.

2.2. Empirical Literature

The empirical studies in this area provide extensive evidence that geopolitical challenges are a noteworthy 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 & Smales (2020) find that stock and bond markets respond adversely to GPRs, but precious metals are resilient under geopolitical challenges. Balcilar et al. (2018) argue that GPRs drive stock market volatility rather than returns for BRICS economies. They also show that the effect of GPRs is particularly strong at return quantiles below the mean. Apergis et al. (2018) demonstrate that GPRs can forecast the dynamics of stock returns and volatility in many companies in the defense industry from 1985 to 2016. Clance et al. (2019) show that GPRs increase the probability of recessions for a sample of 17 advanced countries from 1899 to 2013. Das et al. (2019) conclude that GPRs have robust effects on stock markets in 24 emerging markets from 1997 to 2018. Recently, Wang & Young (2020) prove that an increase of one standard deviation in the monthly number of terrorist attacks results in an increase of more than $50 million in government bond funds and a decline of $75 million in aggregate flows to equity funds.

Other studies point out that geopolitical turbulence can affect financial conditions indirectly through output, investment, trade or consumption, to name a few. Cheng & Chiu (2018) show that GPRs have considerable consequences for the business cycles for almost all emerging economies in the world. In other words, GPRs have created significant contractions of output in their sample. Caldara & Iacoviello (2017) find that GPRs cause slower growth in expected GDP and total factor productivity (TFP). However, Egger & Gassebner (2015) find only a moderate effect of international terrorism on bilateral and multilateral trade and income. Gaibulloev & Sandler (2019) review the impacts of terrorism on GDP, trade, stock exchanges, tourism, and foreign investment. According to their review, there are only trivial impacts to the whole economy, but subsectors such as tourism and investment experience more adverse but rather transient effects.

Regarding methodology, most of the literature on the relationship between geopolitical risk and financial market employs linear models. To overcome some weaknesses of linear model, some recent studies use non-linear models to investigate the impacts of geopolitical risks on macroeconomy. Yurteri Kösedağlı & Önder (2021) apply spatial modelling to examine the drivers of financial instability in emerging economies and find a significant impact of geopolitical risks. Another line of research makes use of quantile regression models. Namely, the work of Balcilar et al. (2018) use quantile regression for examining the role of geopolitical risks to stock market dynamics in the BRICS countries. However, they do not base their analysis on panel data, which may have more information in comparison a time series approach (for single cross-section) in modelling financial dynamics (Hsiao, 2007). Caldara & Iacoviello (2022) explore the prediction capacity of geopolitical risks on GDP growth, TFP growth and military expending. They detect heterogenous impacts of geopolitical risks over quantiles on their dependent variables.

Despite some important findings in the empirical literature, there are three nontrivial gaps: the quantification of GPRs and FS, the estimation methods, and the extent of coverage. Our paper aims to fill these gaps by addressing all of the above-mentioned challenges. First, we utilize the GPR index computed by Caldara & Iacoviello (2017) because of its clear advantages in quantifying consistently GPRs across countries at monthly frequency. Second, we compute the FS based on the approach of Balakrishnan et al. (2011), which has been extended by Park & Mercado Jr (2014) and currently applied by Asian Development Bank (ADB, 2021). This index not only covers a wide range of the subsectors in financial markets, but it also can be extended to many emerging economies for a long time horizon at a monthly frequency. Third, regarding estimation method, we use quantile regression analysis. Although this method offers a high level of flexibility in modeling financial time series, it has been barely used in FS research. Most studies in this area focus on very specific parts of the financial system or a specific group of countries. Finally, by dividing the overall financial sector into different subsectors: stock markets, the debt market, foreign exchange markets, and the banking industry, we can determine the implications of GPRs for these core parts of the financial system in detail. Saisana &

Tarantola (2002) and European Commission & OECD (2008) argue that using subindicators is a pragmatic solution for addressing some weaknesses of composite indicators, such as offering too simple policy advise.

3. Model and Data

This part presents our methodology with two approaches—a fixed-effects panel data model and a quantile panel data model. Afterwards we clarify the advantages of our selected GPRs and how FS is constructed. Finally, we report the data description.

3.1. Econometric model

We use quantile regression method to investigate the geopolitical risks and financial instablity relationship at deeper level. Quantile regression considerably expands the estimating options beyond the conditional mean analysis provided by traditional least squares method (Xiao 2012, Uribe & Guillen 2020). In other words, quantile regression provides insights not only on average or mean-to-mean relationships, but also 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 average modeling is particularly useful because the relationship between GPRs and financial markets can be very different during tranquil and turbulent periods of the market, resulting in very different responses to a potential threat. Thus, quantile regression is a promising tool to investigate the complicated relationship underlining many economic phenomena and beyond (Uribe & Guillen, 2020).

Uribe & Guillen (2020) summarize several other properties that make quantile regression useful for studying financial time series. For example, quantile regression is robust to outliers. Moreover, as a semi-parametric method, it does not require strict distributional assumptions as a conventional linear model does. In addition, quantile regression is robust to a rather heterogeneous error structure or an error structure that is not specified by

Gaussian processes. These advantages make quantile regression a preferable choice over linear models in examining the dynamics in financial markets (Uribe & Guillen, 2020).

Despite its weaknesses in modelling the geopolitical risks and financial stress relationship, fixed effects model is used at the first place due to two reasons. First, we want to verify major findings in the literature on the drivers of FS in emerging economies. Second, the standard fixed-effects panel data model might work as a benchmark analysis. This model is a reference point for another methodological approach, namely, our quantile regression analysis in the next part. In our model specification, we make use of an array of control variables which are extensively used in the financial stress literature (cp. Park & Mercado Jr 2014 and Balakrishnan et al. 2011, and Das et al. 2019). These control variables include the contagion of financial conditions in other emerging and advanced economies, global control variables, country-specific variables, economy and year fixed effects. The concern on reverse-causality or endogeneity of GPRs in FS regression is largely mitigated. This is because GPRs, which are highly relevant to conflict events, are almost exogenous to financial conditions.

After estimating the standard panel regression model, we conduct a quantile regression analysis for panel data, which reflects a methodological contribution of our paper. There are several recently developed quantile regression estimators for panel data (see Santos Silva (2019), Machado & Silva (2019), Galvao & Kato (2017) for a short review). In this paper, we use the approach developed by Machado & Silva (2019) which is a quantile regression model with individual ("fixed") effects. Firpo et al. (2009) name the approach of Machado & Silva (2019) as "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 are determined conditional on the control variables. Compared to other "conditional" quantile regression approaches in the literature, Machado & Silva (2019)'s approach has several advantages such as simple computation, allowing fixed effects to impact the entire distributions, applicability for non-linear models with multiple endogenous variables (Machado & Silva, 2019). The general model is specified as in Machado & Silva (2019):

$$Y_{t,m} = \alpha_m + \beta X_{t,m} + (\theta_m + Z_{t,m}\gamma)U_{t,m}$$

where $(\alpha, \beta, \theta, \gamma)$ denote unknown parameters, Z is a k-vector of the transformations of the components of X as the vector of exogenous independent variables, for element l, $Z_l = \underline{Z}_l(X)$ $(l = 1, 2, 3, ...k)$. Country fixed effects 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$-\tau$ country fixed effect (distribution effect) being $\alpha_m(\tau) \equiv \alpha_m + \theta_m q(\tau)$. This effect might change over different quantiles$-\tau$. With $Z = X$:

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

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 & Silva (2019) propose the quantiles-via-moments approach. Their procedure includes two fixed effects regressions to obtain β and γ, simple calculations for α and θ, and a computation of a univariate quantile. The authors acknowledge that their proposed approach is still inconsistent in case number of cross-section units n and number of time units T are small (incidental parameters problem), however, one of its advantages is that the implementation is quite easy. Furthermore, their simulation exercise shows that the bias has been significantly mitigated 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 (recentered) influence function (RIF). RIF is calculated for unconditional quantile of Y as:

$$RIF(Y, q(\tau)) = q(\tau) + \frac{\tau - I(Y \leq q(\tau))}{F_Y(q(\tau))} \tag{3}$$

where $q(\tau)$ refers to the value of Y at the quantile- τ, F denotes the cumulative distribution function of Y, and $F_Y(q(\tau))$ represents the probability density function of Y at the corresponding quantile, and $I(Y \leq q(\tau))$ is an indicator variable to identify whether an outcome value Y is less than or equal to $q(\tau)$. To implement this estimation, Firpo et al. (2009) suggest three-step procedure. The first step is to calculate RIF for each τ of interest, then by using kernels to estimate density $F_Y(q(\tau))$, and finally to run regression model of $RIF(Y, q(\tau))$ on the control variables.

It should be noted that CQR and UQR are based on two different concepts, therefore a direct comparison of the magnitude of coefficients, between the two approaches should be done cautiously. For example, the results of CQR in Table 4 show that the effect of GPRs estimated at the 70th quantile is higher than that at the 10th quantile. This shows that GPRs increase the within-group dispersion, 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 would increase the overall dispersion of FS as indicated by the disparity between the 70th and the 10th quantiles of the unconditional FS dispersion. Because CQR and UQR address different issues, it is very natural that they might provide different estimation results at different quantiles (see Firpo et al. (2009) and Borah & Basu (2013) for illustrative examples).

In this paper, we prefer CQR over UQR, because CQR has enjoyed a high popularity and well-established status in the literature. The CQR approach has a long history dating back to 1970s with the seminal work of Koenker & Bassett Jr (1978) and is seen by many as the best-known quantile method. We acknowledge that UQR has also sound methodology and has some advantages over CQR such as UQR's high relevance to policy-making process (Borah & Basu, 2013). However, our analysis aims to detect the different reactions of financial stress over different quantiles but not a marginal effect of GPRs on financial stress, therefore, CQR fits perfectly to our research purpose. Moreover, to avoid too strong focus on methodological discussion, which is beyond our purpose, we employ CQR as major method and UQR only to provide further insights to the readers.

3.2. Data construction and description

Our sample includes 17 major emerging economies from 1985 to 2019. The economies investigated in our sample are 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

To measure GPRs, we extracted data for emerging economies from Caldara & Iacoviello (2017). Country-specific GPR indices are computed based on the number of articles related to GPRs divided by the total number of published articles for each month since 1899 in three major newspapers; The New York Times, the Chicago Tribune, and The Washington Post. For country-specific GPR index, the articles are considered as geopolitical-related when they include two groups of phrases. First, the articles must include the most important words (and their variants) relevant to geopolitical threats or acts. These search words should cover general geopolitical topics: such as war (e.g.: “conflict”, “hostilities”, “uprising”, “geopolitical”), peace (e.g. “peace”, “treaty”), military (e.g. “military”, “missile”, “troop”, “weapon”, “bomb”), nuclear (e.g. “nuclear war”, “atomic war”, “nuclear test”), terrorism (e.g. “terror”, “guerrilla”, “hostage”), or actor (for example: “allies”, “army”, “rebels”). Second, the articles must include the country name or the name of its major cities.

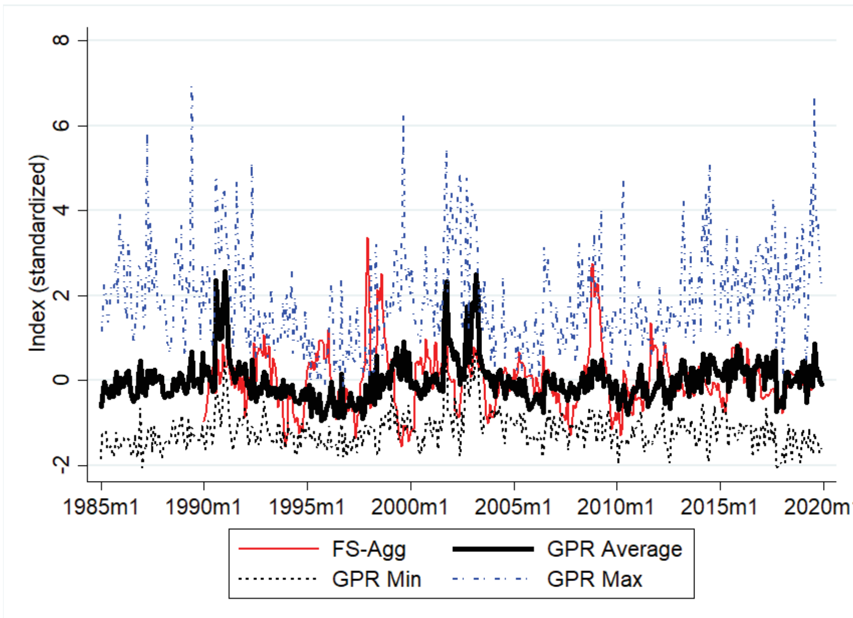
We base our analysis on the GPR index computed by Caldara & Iacoviello (2017) because it has some advantages compared to International Crisis Behavior database (ICB), which counts only military-security crises, in quantifying GPRs. First, in comparison with ICB, the GPR index can provide a more accurate picture of how investors perceive geopolitical instability. This is because the GPR index is based on major newspapers, which 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 better than the number of crises recorded by historians or researchers, who might find it difficult 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, which counts only actual events. This is particularly important today when geopolitical tensions directly or indirectly reflect complex issues, such as trade disputes and climate change, which are highly relevant to geopolitics, but do not cause actual military conflicts. Furthermore, at a high frequency, such as monthly or daily, conflicts can be recorded better by GPR than by ICB because the start and the end dates of actual conflicts are not always clear.

In the literature, the use of ICB and similar datasets on terrorist events is often associated with the event study method (see e.g. Chesney et al. (2011) and Petrov et al. (2019) for examples). Some limitations of the event study approach, such as potential bias in sample selection or imprecise identification of events on a timeline (MacKinlay, 1997), become more noticeable in our research context. That is, it is hard to collect data on terrorist or conflict events with high accuracy for a large number of emerging economies across many years. This makes a comprehensive event-based analysis of the GPR–FS relationship more challenging.

Furthermore, the use of event-based indicators might be less useful than media-based indicators for policymakers and investors. First, it is hard to monitor regularly the geopolitical uncertainties based merely on event database. The events are recorded only when they occur, but in reality, the effects on financial markets can be felt much earlier because market actors can anticipate. Second, it is hard to use event-based indicators to measure or evaluate the development of situation — we can base on number of deaths, injured or monetary damages — but these numbers are often lagged or inaccurate or incomparable. Different from Chesney et al. (2011), who subjectively select some major terrorism events, we contribute to the literature by using media-based GPR index, which is computed at a monthly basis for all emerging markets.

Following Caldara & Iacoviello (2017), our variables are standardized for the convenience of interpretation and comparison. Figure 1 shows the diverse dynamics of geopolitical vulnerability in emerging economies with the periods related with the collapse of the Soviet Union, the turn of the century, global financial crisis, and recent years being the most challenging times. The notable differences indicate the varied nature of emerging economies regarding geopolitical situation.

Figure 1: Geopolitical Risks Index: 1985-2019



3.2.2. Aggregate and subsector FS indices

We compute an FS index for all major emerging economies from 1985 to 2019. Measurement of FS has attracted a great deal of attention from academic and policy perspectives. An index of financial conditions conveys important signals of the economy's health, and it can drive economic intervention policies and market dynamics (for recent examples, see Afonso & Jalles (2020) for the responses of sovereign indebtedness to different financial conditions, IMF (2021a) for how the global financial stability is evaluated through financial conditions barometer).

In the literature, there are three popular indices used to quantify FS[2]. Duprey et al. (2017) construct FS indices for EU countries, which are used by the European Central

[2]Because of the similarity in the construction and usage, throughout this manuscript, we use "financial stress", unfavorable financial condition, and financial instability interchangeably.

Bank to monitor financial developments in Europe (European Central Bank, 2021). The benchmark index comprises the performance of the stock price index, 10-year government bond yields, real effective exchange rates, banking sector stress, and the housing market. Extending their approach to emerging economies might be difficult because of the limited availability of data in the developing world. Another approach is by Koop & Korobilis (2014), who implement a factor model to construct financial conditions for many countries. Their method has been applied by the International Monetary Fund to measure financial situations in major economies or regions of the world (IMF, 2017). To construct the FS index, Koop & Korobilis (2014) make use of corporate spreads, term spreads, inter-bank spreads, sovereign spreads, changes in long-term interest rates, equity and house price returns, equity return volatility, the change in the market share of the financial sector, and credit growth. Their approach yields a comprehensive index rather than a separate look at the segments of financial systems. However, extending their approach to many emerging economies over several decades might be problematic, because getting long-term data for different countries might be difficult. Another index, the Office of Financial Research (OFR) index (OFR, 2021), covers three geographical regions: the US, other advanced economies, and emerging economies. It is based on five financial indicators: credit, equity valuation, funding, safe assets, and volatility. This index might be appropriate for showing regional rather than country-level variations.

Borrowing ideas from Balakrishnan et al. (2011), Park & Mercado Jr (2014), and ADB (2021), our quantification of FS constructs a comparable and complete dataset for all major emerging economies, addressing the challenges for measurement noted above. This approach provides great potential for constructing the financial situations of the countries. The subcomponents of this index include banking sector β (*FS-Bank*), currencies market (*FS-EMPI*), debt market (*FS-Bond*), stock market return (*FS-Stock-rtn*), and stock market volatility (*FS-Stock-vol*). 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. The construction of subsector FS indices are presented below:

1- Banking sector β measures how risky the banking sector is in comparison with the whole market. That is, it quantifies 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 on the banking industry risk.[3]

$$\beta = \frac{cov(r, m)}{var(m)} \tag{4}$$

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. Possible, other candidates to proxy for banking sector stress could be the banking sector sotck volatility, the slope of the yield curve as the difference between the short- and long-term yields on government issued securities or TED spread as the difference between interbank rates and the yield on Treasury bills (e.g. Cardarelli et al. 2011). However it is hard to obtain data for such variables, which should comprise a large sample of major emerging economies over some decades. Therefore, we follow the practice of Asian Development Bank (ADB, 2021) and include only banking sector β to measure the risk of this sector. This approach is also applied for other subsector FS indexes below.

2- *EMPI* measures the depreciation of the local currency with respect to US dollar and the reduction in foreign exchange reserves. High EMPI index signals potential stress in 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:

$$EMPI_{i,t} = \frac{(\Delta e_{i,t} - \mu_{i,\Delta e})}{\sigma_{i,\Delta e}} - \frac{(\Delta RES_{i,t} - \mu_{i,\Delta RES})}{\sigma_{i,\Delta RES}} \tag{5}$$

[3]Some studies define a threshold of β to determine stress level, by recoding β from continuous values to binary (0 and 1) or (0 and positive) or (0 and negative) (e.g. Cardarelli et al. 2011, Balakrishnan et al. 2011). We keep the original values of β and do not convert it 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 with very different baking sectors, (3) a conversion may distort the aggregate financial stress index which will be constructed in the next step. Therefore, we keep the banking β in levels as implemented by Asian Development Bank as well (ADB, 2021).

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, there are many ways to measure sovereign risks (e.g. Popescu & Turcu 2017, Singh et al. 2021). We use the sovereign yield spreads to have more available data. A large yield spread may reflect instability in the debt market.

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

$$\textit{Stock-rtn}_{i,t} = ln(Stock_{i,t}) - ln(Stock_{i,t-12}) \tag{6}$$

Stress of the stock market return is computed by multiplying the *Stock-rtn* by minus one, so that higher FS in stock market means a decrease in stock return. Drops in stock return raise significant concerns on the financial condition.

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

$$\sigma^2 = \omega + \phi_1 \varepsilon_{t-1}^2 + \phi_2 \sigma_{t-1}^2 \tag{7}$$

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 stock market threaten the financial stability.

There are several ways to construct a composite FS index: simple averaging of component indices, variance-equal weights, and principal component analysis. The simple average approach is easy to compute, but it might be biased toward some extreme values for the FS in certain subsectors. A variance-equal weighting procedure can be more representative than the simple average approach, but it might be arbitrary in the selection of weighting methods. One popular weighting method is to use the size of the component financial sectors out of the whole financial market, but such weights are not available for all examined countries for the whole time period. Moreover, Park & Mercado Jr (2014) argue that the variance-equal weighting method often produces erratic and volatile patterns. Based on the practice of ADB (2021) and Park & Mercado Jr (2014), we construct the aggregate FS index using principal component analysis with Hodrick–Prescott highpass filter for standardized subsector FS indices. Following Park & Mercado Jr (2014), we first deploy two components of the principal component analysis to represent the overall dynamics of financial conditions.

Figure 2: Aggregate Financial Stress Index: 1985-2019

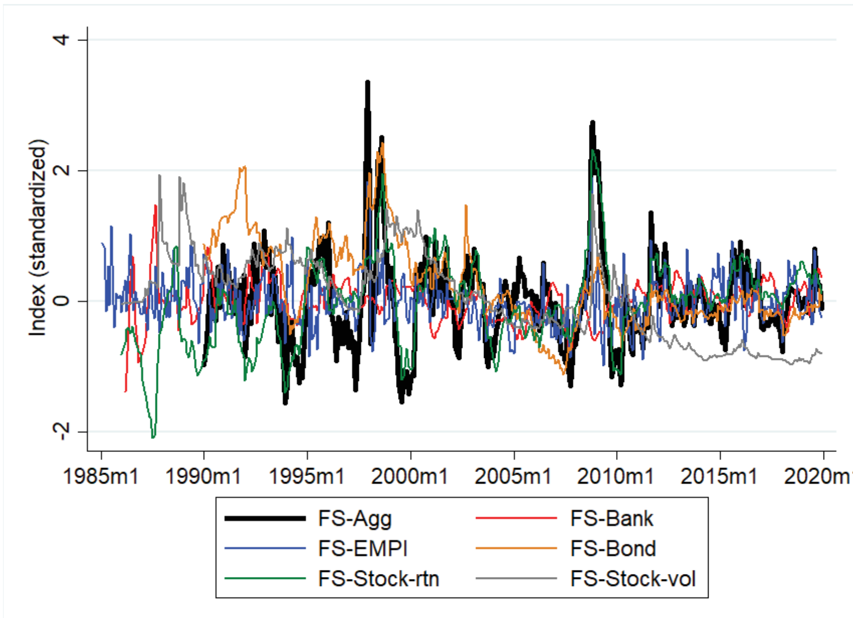


Figure 2 illustrates our aggregate FS indices over time. The most turbulent times for most emerging economies are around the global financial crisis. Other stressful times are at the regional or country level, such as the Asian financial crisis, the Russian default, the Brazil crisis in 1997–1998, the Turkish stock market crash, the outbreak of SARS, and economic crises in Argentina and some other Latin American economies in the early 2000s. Regarding subsector dynamics, Figure 2 shows that stress levels across subsectors are quite different and sometimes deviate from the overall market, especially in the episodes with high instability. This encourages us to scrutinize the geopolitical risks and financial stress relationship not only at the aggregate but also at subsector levels.

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) and Park & Mercado Jr (2014). 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 at a yearly frequency.[4] As a common practice in the literature, some control variables are in first-difference transformation in case of unit root concerns for data in the original form.

3.2.3. Data Description

Table 3 reports descriptive statistics and sources of our data. 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, which are different across the countries. We test for stationarity of our time series by using Dickey-Fuller for univariate data and Pesaran's unit root test in presence of cross section dependence for panel data (Pesaran 2007, Dickey & Fuller 1979). The results of unit root tests demonstrate that the null hypotheses of the unit root are rejected at a 5% significance level for all tests.

4. Empirical Results

This section presents our major findings on the unfavorable and diverse effects of GPRs on financial conditions in emerging and advanced economies.[5]

4.1. GPRs and FS in Emerging Economies: Fixed-Effects Model

In this section we discuss the results with fixed-effects estimator. Table 2 shows that GPRs matter greatly to FS in emerging economies. One standard deviation increase in

[4]Park & Mercado Jr (2014) interpolates yearly data to create monthly data to examine the determinants of FS. In our analysis, the main interests are not to investigate the determinants of FS, moreover, the interpolation methodology normally does not show the real data, thus we keep the economy-specific control variables at their original frequency.

[5]In the tables, we report analytical standard errors. Following a similar procedure of Machado & Silva (2019) and Firpo et al. (2009), we also conducted regression with bootstrapped standard errors clustered at the economy level (100 replications) and find major results qualitatively similar with those using analytical standard errors. However, 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), the interpretation based on clustered standard errors might be too conservative.

Table 1: Data Description

Variable	Obs.	Mean	Std.	Min	Max	UR stat.	Test	Fre.	Sources
FS-Agg.	4002	0	1	-4.53	8.96	-16.27***	pescadf	M	Datastream
FS-Bank	5536	0	1	-4.45	6.28	-13.12***	pescadf	M	Datastream
FS-EMPI	6941	0	1	-12.4	13.2	-20.06***	pescadf	M	Datastream
FS-Bond	4122	0	1	-3.07	5.4	-3.17***	pescadf	M	Datastream
FS-Stock-rtn	6336	0	1	-5.19	3.91	-10.78***	pescadf	M	Datastream
FS-Stock-vol	6336	0	1	-1.63	10.20	-7.00***	pescadf	M	Datastream
GPRs	7140	0	1	-2.07	6.94	-13.00***	pescadf	M	CI
Glo.Com.Pr	7140	0.34	3.40	-15.4	17.0	-14.65***	DF	M	WB
Glo.Eco.Act.	7140	0.04	0.38	-2.17	1.14	-7.04***	DF	M	DFED
Glo.LIBOR	6919	-0.02	0.25	-1.59	1.24	-16.2***	DF	M	FRED
GDP-gr	7068	4.29	4.25	-14.5	17	-5.85***	pescadf	Y	WB
Fiscal-acc.	6792	-1.93	4.16	-17.2	29.8	-2.50***	pescadf	Y	WB
Balance-acc.	7056	0.70	5.39	-20.8	27.4	-2.86***	pescadf	Y	WB
Fin.Open.	6804	.004	0.09	-0.59	0.59	-3.50***	pescadf	Y	WB
Trade.Open.	6888	0.72	8.37	-41.8	84.3	-6.18***	pescadf	Y	WB

*, ** and ***: significance at 10%, 5% and 1%, respectively, for unit root tests (UR).

DF: Dickey-Fuller test with trend. pescadf: Pesaran (2007) test, lagged 2 (4) for yearly (monthly) data.

DF Null: Variable contains a unit root. Pescadf Null: All panels contain unit roots.

Fre.: Frequency of data, monthly (M) or yearly (Y). CI: Caldara & Iacoviello (2017)

FRED: FED of St. Louis. DFED: Dallas FED extended from Kilian (2009). WB: World Bank

GPRs causes between 0.033 (model 5) and 0.085 (model 1) standard deviation increase 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 one-percent decline in GDP growth. Our models explain about 34% of the dynamics of the financial situations of emerging economies, comparable to previous studies, such as Park & Mercado Jr (2014).

Regarding control variables, Table 2 qualitatively confirms some major findings shown in Park & Mercado Jr (2014) and Balakrishnan et al. (2011), which also cover all major emerging economies. The significant effects of global economic activity, GDP growth, and trade openness are as expected. Furthermore, we illustrate that the impacts of contagion from other emerging economies are substantially higher than that from advanced economies. These findings are qualitatively similar to those of Park & Mercado Jr (2014) and Balakrishnan et al. (2011), though the magnitude of these effects is somewhat different.

In addition, our models point out that the contagion of the financial conditions in advanced and other emerging economies holds the most significant explanatory powers for the dynamics of the financial conditions. Specifically, model 2 with only GPRs and contagion explains 33.3%, while the model with all the control variables explains slightly more variability of FS (34.9% in model 5). This might be because our global control variables are the same for all countries and their impacts might be already absorbed by regional FS indices.

Table 3 highlights the impacts of GPRs on different segments of the financial industry. The main findings of Table 2 suggest that there should be at least some notable effects of GPRs on some segments of the financial industry. A deeper investigation of Table 3 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 effects that are not statistically significant (except for the simplest model specification for stock returns). These results suggest that the OLS

Table 2: GPR and Aggregate FS in Emerging Economies: Fixed-Effects Regression (FE)

Model	(1)	(2)	(3)	(4)	(5)
	FS-Agg.	FS-Agg.	FS-Agg.	FS-Agg.	FS-Agg.
GPRs	0.085***	0.044***	0.036**	0.042***	0.033***
	(0.016)	(0.014)	(0.014)	(0.012)	(0.011)
FS-Agg.eme.		0.400***	0.345***	0.402***	0.347***
		(0.058)	(0.027)	(0.058)	(0.054)
FS-Agg.adv.		0.162***	0.099***	0.161***	0.099***
		(0.038)	(0.033)	(0.037)	(0.033)
Glo.Com.Pr.			0.005		0.005
			(0.005)		(0.004)
Glo.Eco.Act.			-0.550***		-0.547***
			(0.155)		(0.156)
Glo.LIBOR			-0.194*		-0.195*
			(0.100)		(0.100)
GDP-gr				-0.028**	-0.028***
				(0.01)	(0.009)
Fiscal-acc				-0.005	-0.005
				(0.006)	(0.006)
Balance-acc				-0.016***	-0.015***
				(0.004)	(0.004)
Fin.Open.				-0.186	0.170
				(0.325)	(0.324)
Trade.Open.				0.006**	0.007**
				(0.002)	(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

*, ** and ***: significance at 10%, 5% and 1%, respectively

Robust standard errors are in round brackets. VIFs: variance inflation factors

Table 3: GPRs and FS in subsectors in Emerging Economies: Fixed-Effects Regression (FE)

Model	(1)	(2)	(3)	(4)	(5)
	FS-Bank	FS-Bank	FS-Bank	FS-Bank	FS-Bank
GPRs	0.021	0.022	0.030	0.023	0.030
	(0.029)	(0.028)	(0.029)	(0.029)	(0.030)
Controls	No	Yes(a)	Yes(a+b)	Yes(a+c)	Yes(a+b+c)
Obs.	5536	5536	5536	5502	5502
R-squared	0.037	0.050	0.054	0.052	0.057
	FS-EMPI	FS-EMPI	FS-EMPI	FS-EMPI	FS-EMPI
GPRs	0.032**	0.031*	0.031**	0.021*	0.021*
	(0.014)	(0.015)	(0.014)	(0.011)	(0.011)
Controls	No	Yes(a)	Yes(a+b)	Yes(a+c)	Yes(a+b+c)
Obs.	6941	6941	6761	6563	6552
R-squared	0.028	0.084	0.092	0.105	0.109
	FS-Bond	FS-Bond	FS-Bond	FS-Bond	FS-Bond
GPRs	0.101	0.099	0.092	0.076	0.069
	(0.059)	(0.059)	(0.058)	(0.053)	(0.053)
Controls	No	Yes(a)	Yes(a+b)	Yes(a+c)	Yes(a+b+c)
Obs.	4122	4122	4122	4122	4122
R-squared	0.268	0.278	0.282	0.319	0.324
	FS-Stock-rtn	FS-Stock-rtn	FS-Stock-rtn	FS-Stock-rtn	FS-Stock-rtn
GPRs	0.067**	0.022	0.021	0.026	0.025
	(0.023)	(0.021)	(0.022)	(0.023)	(0.023)
Controls	No	Yes(a)	Yes(a+b)	Yes(a+c)	Yes(a+b+c)
Obs.	6336	6336	6327	6264	6256
R-squared	0.271	0.385	0.388	0.421	0.423
	FS-Stock-vol	FS-Stock-vol	FS-Stock-vol	FS-Stock-vol	FS-Stock-vol
GPRs	-0.006	-0.020	-0.023	-0.027	-0.029
	(0.024)	(0.023)	(0.023)	(0.025)	(0.025)
Controls	No	Yes(a)	Yes(a+b)	Yes(a+c)	Yes(a+b+c)
Obs.	6336	6336	6327	6264	6256
R-squared	0.378	0.404	0.404	0.418	0.419

*, ** and ***: significance at 10%, 5% and 1%, respectively. Country & Year effects in all models Robust standard errors are in round brackets.

approach might not be sufficient to examine the subtle and complicated relations between financial time series. This encourages us to use quantile regression analysis in the following part to explore further the implications of GPRs on financial conditions.[6]

4.2. GPRs and FS in Emerging Economies: Conditional Quantile Regression

In our sample, the country-specific variables are at an annual frequency while the dependent variables are at a monthly frequency. Furthermore, Table 2 and Table 3 indicate that both country-specific and global control variables contribute slightly to the explanatory power of the model ($R-squared$ remains almost unchanged). Moreover, our analysis does not aim to be a comprehensive investigation of the determinants of FS. Therefore, to keep the model parsimonious without losing the explanatory power and avoid the mixed-frequency of control variables, in the following models, we keep only contagious control variables (FS in emerging and advanced economies). In this section we summarize the results with conditional quantile regression estimator.[7]

Table 4 shows that GPRs do not have statistically significant effects on the FS index at the lowest quantile. The effects are considerably stronger and statistically significant at 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 favorable, GPRs have trivial impacts. In other words, GPRs cannot trigger FS, but they can escalate a worsening situation.

In more detail, Table 4 shows that the impacts of geopolitical uncertainties are diverse through 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. This means that at low quantiles, the greater the GPRs, the higher the FS indices are. The impacts of geopolitical problems become insignificant when the banking industry becomes more unstable. This might be because

[6] Table 3 shows that the R-squared for the regression of stress in banking sector is rather small, indicating that the model specification might be insufficient. However, our main interest is not to comprehensively examine the drivers of the banking sector's performance.

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

Table 4: GPRs and FS in Emerging Economies: Conditional Quantile Regression (CQR)

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

*, ** and ***: significance at 10%, 5% and 1%, respectively.

Control variables: FS indices in other emerging/G7 economies, country & year effects.

Results with other set of control variables are qualitatively similar.

Analytical standard errors are in square brackets.

Results with bootstrapped standard errors are qualitatively similar.

Bootstrapping equality test: test statistics in first row, $p-value$ in second row.

when the banking sector is already under some stress, 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 keeps a holistic approach to managing risk, and it seems to overreact during recent geopolitical unpredictability in Asia. 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 on systematic risk[8].

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 an increase of 0.088 standard deviation in the FS index of the currencies market. This value is remarkably higher than the value of 0.052 found in the overall financial market. In other words, geopolitical problems carry substantial implications for the instability of emerging foreign exchange markets, especially when these markets are already in medium or high stress. These findings are quite similar to those of Petrov et al. (2019), who show strong instant and weekly reactions of the currency markets in India, Israel, South Korea, and Turkey to geopolitical events occurring in those economies. Our regression outcome is also consistent with Salisu et al. (2021), who find the 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 & Iacoviello (2017) find that an increase of one standard

[8] It is often considered that banking sector *beta* smaller than 1 is relatively safe. Therefore, if geopolitical risks increase β, but β value is still under 1, then the concern can be seen as not serious. Moreover, Table 3 shows that our model specification can explain only a limited extent of banking sector β dynamics.

deviation in the GPR index reduces capital flows in emerging economies by 0.23 percentage points, but 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, and higher quantiles see more measurable effects. That is, bond markets are highly vulnerable to geopolitical uncertainties when these markets are already under stress. The consequences of GPRs in this segment are two times 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 have weaker trade, fiscal positions, growth, and government effectiveness. Our findings indicate that GPRs might raise considerable concerns about the capacity or effectiveness of governments in emerging markets in managing risks. Since there is strong evidence of the contagion of sovereign risks, both in the eurozone and globally (see Badarau et al. (2014) for the Eurozone example and Beirne & Fratzscher 2013 for the global evidence), the significant effects of GPRs on the bond market in one country might trigger larger impacts on other countries, especially when the fundamentals are deteriorating during crises and countries are closely connected with others.

In marked contrast to other segments of the financial system, stock markets, regarding both return and volatility measurements, are strong enough 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 also found by Petrov et al. (2019), who conduct a simple descriptive analysis on the link between GPRs and the MSCI World index. Using quantile regression, Balcilar et al. (2018) also show mixed evidence of the consequences of GPRs in BRICS countries: volatility dynamics seem to be more affected than return dynamics. Russia is very vulnerable while India is resilient to geopolitical shocks.

Our findings on stock markets are in contrast with 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 bigger in emerging markets than in advanced markets. However, the event study of Arin et al. (2008) focuses on only six countries, and they consider only major terrorist events. Like Arin et al. (2008), Petrov et al. (2019) show some negative implications of major geopolitical events on stock returns in four emerging markets. In short, 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 countries (mostly those with high vulnerability or great exposure to terrorism). Obviously, the selection bias of these event studies comes from looking only at major events in a few countries and in very recent years.

We use bootstrapping to test the equality of the coefficients across quantiles in the last column of the Table 4. It depicts 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 interpretated cautiously. The CQR standard errors reported in Table 4 (columns Q1 to Q9) indicate that the null hypothesis (the GPRs' coefficient is equal to zeros) 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).[9]

4.3. GPRs and FS in Emerging Economies: Unconditional Quantile Regression

It turns out that 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

[9]The conclusion drawn from our analysis is based on the null hypothesis of GPRs' coefficient equal to zero. It should be noted that the regression result here is based on the conditional quantile function. Different from UQR, CQR only gives information on within- but not between- group dispersion. 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 calculate Z-statistics ($Z = \frac{\beta_1 - \beta_2}{\sqrt{(SE\beta_1)^2 + (SE\beta_2)^2}}$, 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. Note that using z-scores may require some independence assumption of samples, which might be not fulfilled in quantile regression models. Therefore, we prefer bootstrapping test over z-score.

Table 5: GPRs and FS in Emerging Economies: Unconditional Quantile Regression (UQR)

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

*, ** and ***: significance at 10%, 5% and 1%, respectively.

FS indices in other emerging/G7 economies, country & year effects in all models.

Analytical standard errors are in curly brackets.

Results with bootstrapped standard errors are qualitatively similar.

Bootstrapping equality test: test statistics in first row, $p - value$ in second row.

at low and high quantiles, respectively. Moreover, the UQR results show that GPRs have significant impacts on stock returns and volatility, albeit at only certain quantiles.

4.4. GPRs and FS in G7 Economies

Table 6 shows the results for advanced economies, represented by the G7. Because geopolitical events occur mostly in emerging economies, to measure impacts of GPRs in advanced economies, we use global GPRs in our model specification for this part. 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 an increase of around 0.11 standard deviation in the FS index. All coefficients are significant at the 5% level.

One crucial difference between advanced economies and emerging economies is that the impacts of GPRs in advanced economies are similar regardless of the quantile. In other words, geopolitical disorders from emerging economies might affect financial situations in advanced economies in a rather homogeneous pattern. Conversely, as detailed in Table 4, the impacts on emerging economies vary significantly from one quantile to another. Another major difference between emerging and advanced economies is the magnitude of the impacts. The effects of GPRs on the financial conditions of advanced economies are almost three times as high as in emerging economies (for example, 0.120 and 0.047 for advanced and emerging economies, respectively, at the 70th quantile). However, note that the geopolitical risks captured by English-speaking newspapers cover mostly risks or events that occur in emerging economies and exert spillover effects to advanced economies. The captured risks/events may occur in advanced economies as well, but this possibility is negligible. Moreover, because the index aggregates information from sources based in western countries, it may reflect the market sentiment in advanced economies better than the market sentiment in emerging economies. Finally, our advanced-economies sample includes only seven countries and the financial markets in these countries are very complex, which the approach in computing FS for emerging economies might be insufficient. Therefore, a direct comparison of the magnitude of the impacts between advanced economies and emerging economies should be undertaken cautiously.

Several explanations are possible for the differences between emerging and advanced economies regarding the magnitude of the impacts and their pattern over 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 the index only uses English-speaking media outlets. Even though the examined newspapers are popular and have a wide coverage, it should be acknowledged that they might omit 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 makes a large difference with domestic newspapers, which provide more details on the events as well as the relevant context. Several efforts in the literature that use national media sources rather than international ones to investigate the impacts of geopolitical risks on financial market are Jung et al. (2021) and Dibooglu & Cevik (2016).

A second explanation for the different reactions of emerging and advanced economies might be due to their different economic and social nature. Readers of newspapers in emerging economies and advanced economies have different background and country-specific knowledge. Namely, the followers of English newspapers in advanced economies might have less understanding on the geopolitical situations in a typical emerging economy than the local people. While the previous literature on the impacts of geopolitical risks in event studies or single-country analyses, (see e.g. Balcilar et al. 2018), shows that the impacts are strong only in some countries and after some specific events. The impacts in our emerging countries sample may be less pronounced or visible than in advanced countries sample because our sample includes many emerging countries with very diverse development levels, economic structures, or varied resilience levels to the shocks or crises. In contrast, since advanced economies are highly connected with mature financial markets, and have similar economic and social structures, impacts of GPRs on advanced countries might be more homogenous than in emerging economies.

Note that the interpretation based on composite index analysis should be undertaken with care. Composite index might blur the actual contribution or the source of the impacts. Furthermore, analyzing the subsector level also provides more insightful information for the policy makers because they need to know which exact sector needs intervention (European Commission & OECD, 2008). In practice, the policy makers or other actors of the market would like to take comprehensive as well as granular subsector view into account. Therefore, we focus our analysis on the comparison of subsectors.

When we come 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 significant impacts of 77 large-scale terrorist events (around 80% of these events occurred in emerging economies) on advanced economies.

In contrast, other sections of the financial system, such as currencies markets, bond markets, and banking sectors, are almost unaffected by geopolitical uncertainties from emerging economies. This apparent lack of correlation can be justified 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. Moreover, these areas see a dominant role for other advanced economies rather than emerging economies. In other words, these subsectors of all advanced economies are more reliant on the US's subsectors rather than on other emerging economies' subsectors. The banking sectors of advanced economies suffer some disruptive impacts of GPRs at low quantiles.

Taken together, in emerging economies, the effects of GPRs are stronger at low quantiles in the banking sectors, but stronger at middle or high quantiles in the currencies markets and the government bond markets. In advanced economies, the overall effects

Table 6: GPRs and FS in G7 Economies: Conditional Quantile Regression (CQR)

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

*, ** and ***: significance at 10%, 5% and 1%, respectively.

Control variables: FS indices in other emerging/G7 economies, country & year effects.

Results with other set of control variables are qualitatively similar.

Data on EMPI and Bond of the US is the average of other G7 countries.

Analytical standard errors are in square brackets.

Results with bootstrapped standard errors are qualitatively similar.

UQR results are qualitatively similar and can be provided upon request.

Bootstrapping equality test: test statistics in first row, $p - value$ in second row.

of GPRs are substantial and similar across all quantiles of FS. However, in advanced economies, significant effects are witnessed only in the stock markets, not in other segments of the financial systems.

5. Conclusions

Our paper signals that geopolitical disturbances play a prominent role in shaping financial conditions in emerging economies. Further, we investigate which sectors of the financial industry might be more exposed to geopolitical tensions. Our main results show that in emerging economies, foreign exchange markets, and to a smaller degree, the banking and debt sectors might be among the hardest-hit areas. Our quantile analyses prove 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, which are rather robust to external disturbances from geopolitical events. This is in stark contrast to advanced economies, where geopolitical threats have large impacts, but these impacts are concentrated mostly on the stock markets.

These findings could be useful for both political and business decision-makers. Policymakers might see the profound impacts of GPRs on the stability of financial markets. It is recommended that appropriate reaction plans be made against blooming geopolitical uncertainties, especially when the financial markets reveal some stress signals. Moreover, the reaction should consider specific strategies for specific subsectors, because GPRs do not affect all subsectors equally. Investors should consider the fragility of the relevant asset markets when they build up or adjust their portfolios.

Our paper suggests several questions in need of further investigation. For example, future research might explore whether there are threshold effects for geopolitical risks to exert impacts on the FS. This is particularly important to policy makers to prepare intervention plan and investors to adjust their portfolio in case of rising geopolitical threats[10]. Moreover, it is worth investigating the role of GPRs on the duration of FS. This is of vital importance to policymakers and investors to endure vulnerable periods and support

[10]We thank the anonymous referee for suggesting us this interesting research question.

the markets in recovery. Furthermore, future research may use a larger and more comprehensive set of proxies for stress level of subsectors to better reflect the risk levels in these segments. For example, a large set of proxies for banking sector condition, such as lending rate and Treasury bill rates or the non-performing loan ratios of banking sector, should be considered.

References

ADB (2021). Financial stress index. `https://aric.adb.org/database/fsi`. Accessed: 2021-07-30.

Afonso, A., & Jalles, J. T. (2020). Sovereign indebtedness and financial and fiscal conditions. *Applied Economics Letters*, *27*, 1611–1616.

Apergis, N., Bonato, M., Gupta, R., & Kyei, C. (2018). Does geopolitical risks predict stock returns and volatility of leading defense companies? evidence from a nonparametric approach. *Defence and Peace Economics*, *29*, 684–696.

Arin, K. P., Ciferri, D., & Spagnolo, N. (2008). The price of terror: The effects of terrorism on stock market returns and volatility. *Economics Letters*, *101*, 164–167.

Badarau, C., Huart, F., & Sangaré, I. (2014). Sovereign risk premium and divergent fiscal policies in a monetary union. *Revue d'économie politique*, *124*, 867–898.

Balakrishnan, R., Danninger, S., Elekdag, S., & Tytell, I. (2011). The transmission of financial stress from advanced to emerging economies. *Emerging Markets Finance and Trade*, *47*, 40–68.

Balcilar, M., Bonato, M., Demirer, R., & Gupta, R. (2018). Geopolitical risks and stock market dynamics of the brics. *Economic Systems*, *42*, 295–306.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, *121*, 823–866.

Barro, R. J., & Liao, G. Y. (2021). Rare disaster probability and options pricing. *Journal of Financial Economics*, *139*, 750–769.

Barro, R. J., & Ursúa, J. F. (2008). *Macroeconomic crises since 1870*. Technical Report National Bureau of Economic Research.

Baur, D. G., & Smales, L. A. (2020). Hedging geopolitical risk with precious metals. *Journal of Banking & Finance*, *117*, 105823.

BCA Research (2021). Geopolitical strategy. `https://www.bcaresearch.com/macro-research-services/geopolitical-strategy`. Accessed: 2021-05-30.

Beirne, J., & Fratzscher, M. (2013). The pricing of sovereign risk and contagion during the european sovereign debt crisis. *Journal of International Money and Finance*, *34*, 60–82.

Blackrock Investment Institute (2021). Geopolitical risk dashboard. `https://www.blackrock.com/corporate/insights/blackrock-investment-institute/interactive-charts/geopolitical-risk-dashboard`. Accessed: 2021-07-30.

Blanchard, O. J. (1985). Debt, deficits, and finite horizons. *Journal of political economy*, *93*, 223–247.

Blanchard, O. J., Fischer, S., BLANCHARD, O. A. et al. (1989). *Lectures on macroeconomics*. MIT press.

Blomberg, S. B., Hess, G. D., & Orphanides, A. (2004). The macroeconomic consequences of terrorism. *Journal of monetary economics*, *51*, 1007–1032.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, *77*, 623–685.

Borah, B. J., & Basu, A. (2013). Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence. *Health economics*, *22*, 1052–1070.

Caldara, D., & Iacoviello, M. (2017). Measuring geopolitical risk. *Unpublished working paper, https://www2. bc. edu/matteo-iacoviello/gpr_files/GPR_PAPER. pdf*, .

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, *112*, 1194–1225.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*, 414–427.

Caplain, J., Fry, F., & Topping, S. (2017). Navigating the impact of geopolitical change on banking regulation. `https://assets.kpmg/content/dam/kpmg/xx/pdf/2017/12/banks-navigate-uncertainty-with-geopolitical-change.pdf`. Bank and Capital Markets. Accessed: 2021-05-30.

Cardarelli, R., Elekdag, S., & Lall, S. (2011). Financial stress and economic contractions. *Journal of Financial Stability*, *7*, 78–97.

Carney, Mark (2016). Uncertainty, the economy and policy. `https://www.bis.org/review/r160704c.pdf`. Speech at the Bank of England, London, 30 June 2016.Accessed: 2021-05-30.

Cheng, C. H. J., & Chiu, C.-W. J. (2018). How important are global geopolitical risks to emerging countries? *International economics*, *156*, 305–325.

Chesney, M., Reshetar, G., & Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. *Journal of Banking & Finance*, *35*, 253–267.

Clance, M. W., Gupta, R., & Wohar, M. E. (2019). Geopolitical risks and recessions in a panel of advanced economies: evidence from over a century of data. *Applied Economics Letters*, *26*, 1317–1321.

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American journal of sociology*, *100*, 1261–1293.

Das, D., Kannadhasan, M., & Bhattacharyya, M. (2019). Do the emerging stock markets react to international economic policy uncertainty, geopolitical risk and financial stress alike? *The North American Journal of Economics and Finance*, *48*, 1–19.

Dibooglu, S., & Cevik, E. I. (2016). The effect of north korean threats on financial markets in south korea and japan. *Journal of Asian Economics*, *43*, 18–26.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*, 427–431.

Duprey, T., Klaus, B., & Peltonen, T. (2017). Dating systemic financial stress episodes in the eu countries. *Journal of Financial Stability*, *32*, 30–56.

Eckstein, Z., & Tsiddon, D. (2004). Macroeconomic consequences of terror: theory and the case of israel. *Journal of monetary economics*, *51*, 971–1002.

Egger, P., & Gassebner, M. (2015). International terrorism as a trade impediment? *Oxford Economic Papers*, *67*, 42–62.

European Central Bank (2021). Clifs - country-level index of financial stress. `https://sdw.ecb.europa.eu/browse.do?node=9693347`. Accessed: 2021-05-30.

European Commission & OECD (2008). *Handbook on constructing composite indicators: methodology and user guide*. OECD publishing.

Ferguson, N. (2008). Earning from history?: Financial markets and the approach of world wars. *Brookings Papers on Economic Activity*, *2008*, 431–477.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, *77*, 953–973.

Frey, B. S., Luechinger, S., & Stutzer, A. (2007). Calculating tragedy: Assessing the costs of terrorism. *Journal of Economic Surveys*, *21*, 1–24.

Gaibulloev, K., & Sandler, T. (2019). What we have learned about terrorism since 9/11. *Journal of Economic Literature*, *57*, 275–328.

Galvao, A. F., & Kato, K. (2017). Quantile regression methods for longitudinal data. In *Handbook of quantile regression* (pp. 363–380). Chapman and Hall/CRC.

Glick, R., & Taylor, A. M. (2010). Collateral damage: Trade disruption and the economic impact of war. *The Review of Economics and Statistics*, *92*, 102–127.

Hsiao, C. (2007). Panel data analysis—advantages and challenges. *Test*, *16*, 1–22.

IHS Markit (2021). Geopolitical risk intelligence solutions. `https://ihsmarkit.com/products/geopolitical-risk-analysis.html`. Accessed: 2021-05-30.

IMF (2017). Global financial stability report april 2017. `https://www.imf.org/en/Publications/GFSR/Issues/2019/10/11/Global-Financial-Stability-Report-April-2017-Getting-the-Policy-Mix-Right-44509`. Accessed: 2021-05-30.

IMF (2021a). Global financial stability report. https://www.imf.org/en/publications/gfsr. Accessed: 2021-05-30.

IMF (2021b). World economic outlook report. https://www.imf.org/en/Publications/WEO. Accessed: 2021-05-30.

JP Morgan (2019). Geopolitical risks on the rise. https://www.jpmorgan.com/insights/research/geopolitical-risk-on-rise. Accessed: 2021-07-30.

Jung, S., Lee, J., & Lee, S. (2021). The impact of geopolitical risk on stock returns: Evidence from inter-korea geopolitics. *IMF Working Papers*, *2021*.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*, 1053–69.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, (pp. 33–50).

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101–116.

Lenain, P., Bonturi, M., & Koen, V. (2002). The economic consequences of terrorism, .

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, *213*, 145–173.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*, 13–39.

McKinsey (2016). Geostrategic risks on the rise. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/geostrategic-risks-on-the-rise. Accessed: 2021-07-30.

Nakamura, E., Steinsson, J., Barro, R., & Ursúa, J. (2013). Crises and recoveries in an empirical model of consumption disasters. *American Economic Journal: Macroeconomics*, *5*, 35–74.

OFR (2021). Ofr financial stress index. https://www.financialresearch.gov/financial-stress-index/. Accessed: 2021-07-30.

Park, C.-Y., & Mercado Jr, R. V. (2014). Determinants of financial stress in emerging market economies. *Journal of Banking & Finance*, *45*, 199–224.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of applied econometrics*, *22*, 265–312.

Petrov, A., Hentov, E., & Zumbo, F. (2019). How does geopolitics affect financial markets? https://www.ssga.com/investment-topics/general-investing/2018/09/does-geopolitics-affect-financial-markets.pdf. State Street Global Advisors. Accessed: 2021-05-30.

Popescu, A., & Turcu, C. (2017). Sovereign debt and systemic risk in the eurozone: A macroeconomic perspective. *Economic Modelling*, *67*, 275–284.

Powell, J. H. (2019). Challenges for monetary policy. https://www.federalreserve.gov/newsevents/speech/powell20190823a.htm. Speech at the "Challenges for Monetary Policy" symposium, sponsored by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming. Accessed: 2021-05-30.

Presbitero, A. F., Ghura, D., Adedeji, O. S., & Njie, L. (2016). Sovereign bonds in developing countries: Drivers of issuance and spreads. *Review of Development Finance*, *6*, 1–15.

Saisana, M., & Tarantola, S. (2002). *State-of-the-art report on current methodologies and practices for composite indicator development* volume 214. Citeseer.

Salisu, A. A., Cuñado, J., & Gupta, R. (2021). Geopolitical risks and historical exchange rate volatility of the brics. *International Review of Economics & Finance*, .

Sandler, T., & Enders, W. (2008). Economic consequences of terrorism in developed and developing countries: An overview. *Terrorism, economic development, and political openness*, *17*, 1–43.

Santos Silva, J. (2019). *Quantile regression: Basics and recent advances*. Technical Report Stata Users Group.

Singh, M. K., Gómez-Puig, M., & Sosvilla-Rivero, S. (2021). Quantifying sovereign risk in the euro area. *Economic Modelling*, *95*, 76–96.

The Economist (2021). Global risk. https://gfs.eiu.com/Archive.aspx?archiveType=globalrisk. Accessed: 2021-05-30.

Tsai, J., & Wachter, J. A. (2015). Disaster risk and its implications for asset pricing. *Annual Review of Financial Economics*, *7*, 219–252.

Uribe, J. M., & Guillen, M. (2020). *Quantile Regression for Cross-Sectional and Time Series Data: Applications in Energy Markets Using R*. Springer Nature.

Wade, K., & Lauro, I. (2019). Measuring the market impact of geopolitics. https://www.schroders.com/en/sysglobalassets/digital/insights/2019/pdfs/2019_sept_measuring-the-market-impact-of-geopolitics_kw_il_cs1696.pdf. Schroders Foresight. Accessed: 2021-05-30.

Wang, A. Y., & Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics*, *137*, 491–514.

World Bank (2021). Global economic prospects 2021. https://www.worldbank.org/en/publication/global-economic-prospects. Accessed: 2021-05-30.

Xiao, Z. (2012). Time series quantile regressions. In *Handbook of Statistics* (pp. 213–257). Elsevier volume 30.

Yaari, M. E. (1965). Uncertain lifetime, life insurance, and the theory of the consumer. *The Review of Economic Studies*, *32*, 137–150.

Yurteri Kösedağlı, B., & Önder, A. Ö. (2021). Determinants of financial stress in emerging market economies: Are spatial effects important? *International Journal of Finance & Economics*, *26*, 4653–4669.