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Geopolitical risk spillovers and its determinants

Faruk Balli[1,2] · **Hatice Ozer Balli[1]** · **Mudassar Hasan[1,3]** · **Russell Gregory-Allen[1]**

Abstract

Geopolitical risk (GPR) tends to cascade from one country to another. Understanding GPR transmission is important to devising risk management strategies for institutional investors and corporate managers, and national security policies for governments. In this paper, we measure and explain cross-country transmission of GPR. Our sample covers 19 country-based GPR indexes of Caldara and Iacoviello (Measuring geopolitical risk, 2018) from January 1985 to December 2016. We apply the spillover model of Diebold and Yilmaz (Int J Forecast 28:57–66, 2012) to measure pairwise as well as system-wide GPR transmission. The estimation results show a substantial amount of GPR transmission across our sample countries, with certain countries and geographical clusters being more prominent than others. We then explain the pairwise GPR transmission using a cross-sectional regression motivated by a gravity model framework. We find that certain bilateral linkages such as bilateral trade and geographical proximity significantly explain the pairwise GPR transmission. This transmission is positively associated with both countries' debt burdens and geographical sizes, transmitting country's fiscal imbalance, and is negatively associated with recipient country's economic size. The results imply that these factors may be used to predict the trajectory of GPR, which is an important input for the assessment of cross-border investment appraisals as well as international stability initiatives.

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✉ Faruk Balli
  f.balli@massey.ac.nz

  Mudassar Hasan
  mudassar.hassan@lbs.uol.edu.pk

[1] School of Economics and Finance, Massey University, Albany, Auckland, New Zealand

[2] Al-Farabi Kazakh National University, Almaty, Kazakhstan

[3] Lahore Business School, The University of Lahore, Lahore 54000, Pakistan

1 Introduction

In this study, we examine the cross-country spillovers of geopolitical risk (GPR) in the form of information transmission. This is in contrast to the conflict contagion literature, which has overwhelmingly focused on the spread of physical conflicts.

Geopolitical risk (GPR) has become an increasingly complex phenomenon over the past two decades. This complexity is primarily due to the rapidly evolving and globally integrated geopolitical landscape, which has not only broadened the scope of GPR but has also rendered it more contagious. Several geopolitical events such as the Gulf War, the 2003 Iraq invasion, 9/11, the Ukraine/Russia crisis, the terrorist attacks in Paris, the ongoing escalation of the Syrian conflict, the US–North Korea tensions over nuclear proliferation, the Qatar–Saudi Arabia proxy conflict, the USA's recognition of Jerusalem as Israel's capital, the USA's cancelation of Iran's nuclear deal, and the most recent killing of an Iranian commander by the USA and the prompt Iranian revenge show that GPR shocks stemming from a country can transmit to multiple countries. Given that cross-country transmission[1] of GPR plays a critical role in shaping global macro-financial cycles, several international agencies, including the International Monetary Fund (IMF) and the World Bank, have published reports[2] highlighting growing concerns among policymakers, investors, and corporate managers about this issue.

In addition to these widespread concerns, exploring GPR transmission contains predictive relevance to devise better risk management strategies and national security policies because the following trends of wide-ranging and long-term repercussions for GPR are emerging globally (Suárez-de Vivero and Mateos 2017). First, international governance is weakening, and the power centers are shifting from traditional state actors to non-state actors, increasing the prospects of a political crisis. Typically, non-state actors are hostile toward the government, making the overall geopolitical landscape of the country unstable, which increases its GPR. This was obvious throughout the Afghan War as the power shifted considerably from the Afghan government to the Taliban. Second, over the last decade, there has been an unprecedented rise in national sentiment globally, especially in the USA and India, fuelling extremism among the public, a major threat to the global geopolitical landscape. For individual countries, such extremist ideologies are a potential source of both internal and external threats; in India, for instance, this has not only caused a Hindu–Muslim rift internally, but it has also increased hostility in Indo-Pak

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[1] Instead of distinguishing between contagion, spillover, diffusion, and spread, we view GPR contagion as a transmission mechanism/process.

[2] See Global Risks Reports published in 2016, 2017, and 2018; World Economic Outlook, October 2017, and Economic Bulletin, March 2016, published by the World Economic Forum, International Monetary Fund, and European Central Bank, respectively. These reports highlight the growing importance of GPR and its transmission. See Suárez-de Vivero and Mateos (2017) for a good collection of such reports.

relations. Finally, international restrictions on the proliferation of weapons of mass destruction have not produced the intended consequences, especially for Iran and North Korea, further raising the potential for geopolitical tensions between these countries and major economic powers. These global trends are likely to increase GPR and its transmission across the globe concerning financial firms, insurance companies, businesses, and national security advisors who typically track GPR to make forecasts[3] and manage and avoid geopolitical surprises. Such forecasts allow businesses to manage their credit risk, build resilient supply chains, develop crisis response plans, and secure credit and political risk insurance to protect their assets better.

A review of prior literature on the topic reveals that an examination of GPR transmission is necessary to fill a theoretical void. GPR is an essential attribute of geopolitical conflicts. However, the literature overlooks GPR transmission while focusing on explaining or predicting geopolitical conflicts' physical spread. In particular, studies explain how geopolitical conflicts undergo spread, diffusion, or contagion in their physical form (Blomberg and Rosendorff 2006; Braithwaite 2010; Buhaug and Gleditsch 2008; Salehyan and Gleditsch 2006). Some hold media information responsible for the physical transmission of conflicts (Beiser 2013; Hill and Rothchild 1986; Weidmann 2015). Others aim to predict geopolitical conflicts such as interstate wars (Beck et al. 2000; Ward et al. 2007), civil wars (Ward et al. 2010), geopolitical tensions (Chadefaux 2014), or other political unrests like state failures, human rights violations, ethnic conflict, genocide, and political instability (De Mesquita 2010; Gleditsch and Ward 2013; Schneider et al. 2010; Pevehouse and Goldstein 1999; Schrodt and Gerner 2000). Overall, the existing literature focuses mainly on predicting the spread of physical conflicts rather than the spread of GPR that emanates from such conflicts.

Notwithstanding their overwhelming emphasis on the spread of physical geopolitical conflicts, the prior studies have the following shortcomings. First, in explaining that spread, prior studies often rely on event-based data considering conflict contagion during a specific interstate conflict. Such event-based studies provide good hindsight but contain a limited predictive value. Furthermore, their overreliance on single or individual conflicts often ignores the possibility of multiple conflicts coinciding with increased complexity. In reality, many geopolitical conflicts happen simultaneously, especially in a multi-country context, and are often interlinked. Studies aiming to predict geopolitical conflicts also ignore this possibility. Thus, a more sophisticated, network-based approach that can capture such geopolitical complexities is needed. Second, studies employing news-based indicators to predict geopolitical conflicts offer dichotomous or probabilistic forecasts. Binary predictions produce black-and-white forecasts regarding geopolitical conflicts. However, geopolitical conflicts occur more frequently nowadays, so their corresponding GPR is a continuously occurring phenomenon. On the flip side, probabilistic predictions,

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such as Chadefaux (2014), are fraught with imperfections in datasets. Finally, some studies only emphasize a particular region, such as Central Africa (e.g., Huff and Lutz 1974). For studying interstate conflicts, Central Africa had critical importance during the 1970s. However, nowadays, GPR concerns have become progressively rampant across the globe—a trend not likely to subside soon—and other regions, such as emerging economies, have gained such importance.

Fittingly, Caldara and Iacoviello (2018) have recently introduced a broader view of GPR, which encompasses realized geopolitical events and potential threats, thereby accounting for both eventual and probabilistic risk concepts. Providing a continuous, real-time tracking of GPR perceived by a wide range of stakeholders, including the public, the media, investors, and policymakers, the GPR measure captures a broader spectrum of stakeholder concerns reflected in newspapers. Caldara and Iacoviello (2018) developed the GPR index from news stories featuring events and threats associated with geopolitical conflicts such as wars, terrorist acts, ethnic and political violence, and geopolitical tensions. Using the news-based GPR index, we build upon conflict contagion literature, which considers the role of GPR-related news in spreading geopolitical conflicts across borders. Given that GPR shocks stemming from geopolitical events and threats flow across borders via news stories (Beiser 2011, 2013; Hill and Rothchild 1986; Weidmann 2015), we argue that this would result in GPR transmission across countries. Subsequently, we consider another stream of the conflict contagion literature wherein a disease-conflict analogy explains the transmission of geopolitical conflicts, such as political violence (Braithwaite 2010; Buhaug and Gleditsch 2008) and terrorism (Blomberg and Rosendorff 2006). This analogy proposes that the degree to which a conflict spreads varies with the extent of social interaction between two countries successfully captured by a gravity model framework (Buhaug and Gleditsch 2008). The framework has successfully explained cross-country transmission of economic reforms (Fidrmuc and Karaja 2013), stock market volatility (Balli et al. 2015), and economic policy uncertainty (Balli et al. 2017). In the same vein, we use this framework to explain the cross-country transmission of GPR.

In today's predominantly globalized world, the idea of GPR shocks transmitting across countries is more plausible than ever. Since countries are becoming increasingly integrated, global information flows also reflect this trend (Mowlana 1997). The phenomenal growth in I.T., the Internet, and social media networks, such as Twitter, Facebook, and YouTube, has multiplied the speed and scale of information transmission. Global information flows are likely to surge in future (Beiser 2011). These technological advancements would facilitate GPR transmission because people would learn more quickly about foreign conflicts. This would encourage people to emulate those foreign conflicts in their own countries (Hill and Rothchild 1986; Hill et al. 1998) or cause fear about geopolitical conflicts (Kuran 1998), further amplifying GPR transmission.

We invoke a statistically sophisticated approach, the spillover model of Diebold and Yilmaz (2012), to examine GPR transmission across 19 countries. To further decompose our results into short- and long-term GPR transmissions, we follow Baruník and Křehlík's (2018) frequency-connectedness model. This model allows

us to examine spillovers of GPR shocks short term (up to 3 months) and long term (between 3 and 100 months). Finally, we explain the pairwise GPR transmission by a gravity model. We find a substantial GPR transmission across our sample countries, with some countries and geographical clusters more prominent than others. A cross-sectional analysis, motivated by a gravity model framework, is utilized to explain the pairwise GPR transmission, revealing that bilateral linkages and country-specific factors are essential in driving GPR transmission. The overall findings are robust to controlling for the short- and long-term time horizons.

This study contributes to the literature in the following ways. First, we propose a novel perspective by studying GPR transmission via information flows associated with geopolitical conflicts. This contrasts with the previous studies that have considered the role of information flows in spreading physical conflicts (e.g., Beiser 2013; Hill and Rothchild 1986; Weidmann 2015). Second, we point out the potential factors to help predict the trajectory of GPR transmission. In this way, we contribute to the studies offering dichotomous and probabilistic predictions and highlighting conditions most conducive to geopolitical events (Fearon and Laitin 2003; Glaser 2000; Huth 2009; Powell 2004). Third, instead of using a latent variable such as cross-country events that could denote information transmission, we observe actual information flows by involving news-based GPR indices introduced by Caldara and Iacoviello (2018). The GPR indices should improve GPR transmission reliability by overcoming the data imperfections found in Chadefaux (2014).

In contrast to Chadefaux (2014), which aimed to predict wars by relying on a measure of geopolitical tensions, we indicate bilateral linkages and country-specific factors that may explain GPR transmission. Fourth, we build upon Huff and Lutz (1974), who considered only Central African countries for their analysis. We apply a robust statistical analysis to a sample of 18 emerging economies and the USA, thereby providing empirical evidence from a completely different context. Finally, we point out a new type of informational spillover, i.e., GPR spillover, apart from the ones already introduced by the literature (Balli et al. 2015, 2017; Fidrmuc and Karaja 2013).

This study includes the following sections. Section 2 lays out the methodological details and dataset. Section 3 reports empirical findings and discussion. Section 4 concludes.

2 Data and methodology

2.1 Dataset

We use the monthly series of the newly constructed GPR indices (Caldara and Iacoviello 2018) for 19 countries. Data are obtained from the economic policy uncertainty Web site (http://www.policyuncertainty.com)[4] from January 1985 to

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[4] For the USA, the Web site also contains other components of GPR index such as GPR_Threat, GPR_ Act, GPR_Narrow, GPR_Broad, and GPR_Nuclearthreat. However, to ensure consistency in our analysis, we use the 'benchmark' GPR index for the US.

December 2016. Based on data availability, our sample countries include Argentina, Brazil, China, Colombia, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Russia, Saudi Arabia, South Africa, Thailand, Turkey, Ukraine, USA, and Venezuela. Data on certain bilateral and country-specific factors, which we consider as potential determinants of pairwise GPR transmission, are also collected over the same period. The bilateral factors include bilateral trade, colonial ties, contiguity, common language, and geographical distance between the two countries. The country-specific factors are the central government's debt, budget deficit, stock market capitalization, and each country's geographical area. Appendix A, given at the end, describes these variables along with their data sources.

As we have already highlighted in Sect. 1, Caldara and Iacoviello (2018) consider a broader view of GPR, which encompasses realized geopolitical events and potential threats, thereby accounting for both eventual and probabilistic risk concepts and tracking of GPR perceived by a wide range of stakeholders, including the public, the media, investors, and policymakers. Accordingly, Caldara and Iacoviello (2018) developed the GPR index from news stories featuring events and threats associated with geopolitical conflicts such as wars, terrorist acts, ethnic and political violence, and geopolitical tensions. The authors identified six groups of keywords capturing various GPR dimensions,[5] namely explicit mentions of geopolitical risk and military-related tensions (Group 1), nuclear tensions (Group 2), war threats (Group 3), terrorist threats (Group 4), and actual adverse geopolitical events (Groups 5 and 6). This allowed Caldara and Iacoviello (2018) to disentangle the GPR Acts, which is related to adverse geopolitical events (Groups 5 and 6), from the pure GPR Threats (Groups 1 to 4). However, the benchmark GPR index, which we consider in this study, accounts for both types of GRPs.

To create the GPR index, Caldara and Iacoviello (2018) gathered articles from electronic archives of 11 newspapers: The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. These globally renowned newspapers belong to English-speaking nations, namely the USA (6), Britain (4), and Canada (1). For each newspaper, the

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[5] According to Caldara and Iacoviello (2018), the following keywords are used to capturing six dimensions of GPR: Group 1 [(Geopolitical AND (risk* OR concern* OR tension* OR uncertain*) "United States" AND tensions AND (military OR war OR geopolitical OR coup OR guerrilla OR warfare) AND ("Latin America" OR "Central America" OR "South America" OR Europe OR Africa OR "Middle East" OR "Far East" OR Asia)];

Group 2 [("nuclear war" OR "atomic war" OR "nuclear conflict" OR "atomic conflict" OR "nuclear missile*") AND (fear* OR threat* OR risk* OR peril* OR menace*)];

Group 3 ["war risk*" OR "risk* of war" OR "fear of war" OR "war fear*" OR "military threat*" OR "war threat*" OR "threat of war" ("military action" OR "military operation" OR "military force") AND (risk* OR threat*)];

Group 4 ["terrorist threat*" OR "threat of terrorism" OR "terrorism menace" OR "menace of terrorism" OR "terrorist risk" OR "terror risk" OR "risk of terrorism" OR "terror threat*"];

Group 5 ["beginning of the war" OR "outbreak of the war" OR "onset of the war" OR "escalation of the war" OR "start of the war" (war OR military) AND "air strike" (war OR battle) AND "heavy casualties"];

Group 6 ["terrorist act" OR "terrorist acts"].

authors collect monthly counts of GPR-related articles as a proportion of the total number of articles. Subsequently, the authors divided each monthly count by the mean (from 2000 to 2009) of the series and multiplied it by 100 to obtain normalized GPR index.

Since the newspapers considered by Caldara and Iacoviello (2018) only belong to three countries, one might narrowly interpret the index as the GPR perceived only in the USA, the UK, and Canada. However, the authors argue that their sample newspapers have broader geographical coverage and regularly report geopolitical news involving other countries, leading to an interpretation that the GPR index successfully captures the geopolitical risks of other countries as well.

We use GPR indices for the following reason. Existing GPR proxies lack certain features that a GPR indicator should have to be used to measure GPR transmission. A GPR index equipped with these features broadens GPR transmission scope by enabling us to capture geographically broad, historically long, and sufficiently frequent interactions among GPRs of multiple countries. In general, other indicators that may have served as a proxy for GPR are fraught with geographic scale, history, and coverage limitations. Also, those proxies are either hard to quantify, rely on single wars and hindsight, or fail to capture equally important instances when peace prevailed instead of war (Leetaru 2011).

Furthermore, some indicators are less frequent and fail to track or anticipate mounting tensions and conflict outbreaks in shorter periods (Beck et al. 2000, 2004; De Marchi et al. 2004; Gleditsch and Ward 2013). Others are not standardized and therefore are not comparable across countries. Another critical issue with the existing GPR proxies (such as political unrest, war, and conflict) is that they reflect a narrow view of GPR. On the other hand, the GPR index has a much broader scope surrounding all sorts of geopolitical conflicts, which can overcome these limitations allowing us to better capture cross-country GPR transmission dynamics.

The GPR measure of Caldara and Iacoviello (2018) controls for these shortcomings. The index is developed from news information, the product of fast and accurate coverage of GPR-related stories worldwide, making it an accurate and timely measure of GPR. The index also avoids the problem of hindsight while reflecting the most recently published news content. It should also be noted that newspapers have an essential advantage over the event-based data to report GPR even when no actual event occurs. Therefore, the GPR index is a robust measure of GPR and carries better predictive content for the sake of forecasting GPR. This index is also broad in terms of geographic and historical coverage. It offers a frequent, long-term GPR series for many countries; the monthly GPR series has been available for 19 countries since 1985. The more data we have on GPR, the better it becomes to capture GPR transmission. The index is also a sufficiently broad measure of GPR, for rather than tracking a single or a certain kind of conflict, it captures news information on multiple conflicts simultaneously. Thus, the GPR indices used in this study broaden the scope of GPR transmission by allowing for fluctuations in the level of GPR within and across countries, and hence ensuring reliable inferences and better insights into the (cross-country) effects exerted—a point that we owe to Caldara and Iacoviello (2018).

Table 1 Descriptive statistics of GPR series

	Mean	Median	Max	Min	SD	Skew	Kurt	J.B.	ADF	Sample size
Argentina	111.85	104.23	371.01	36.40	43.62	1.43	7.03	432.96***	− 8.27***	384
Brazil	103.94	100.35	221.41	43.02	29.99	1.01	4.59	116.99***	− 6.38***	384
China	105.60	98.21	251.23	56.53	29.84	1.40	5.40	240.54***	− 5.03***	384
Colombia	80.31	77.84	171.85	22.78	28.53	0.53	3.31	21.70***	− 4.65***	384
India	93.58	85.36	247.40	45.01	29.44	2.17	9.69	1126.15***	− 4.99***	384
Indonesia	74.52	68.64	275.94	20.20	31.86	1.49	7.34	491.68***	− 3.20***	384
Israel	84.52	80.74	179.20	45.78	22.79	1.16	4.59	140.45***	− 4.23***	384
South Korea	108.73	101.23	274.42	38.70	38.79	1.50	6.51	378.73***	− 8.80***	384
Malaysia	90.11	84.17	278.88	17.49	35.12	1.68	8.34	706.90***	− 7.45***	384
Mexico	99.08	92.55	214.35	55.03	26.08	1.20	4.74	156.12***	− 5.04***	384
Philippines	99.28	92.50	215.54	35.25	35.52	0.81	3.35	48.67***	− 4.45***	384
Russia	105.86	100.15	241.38	47.68	29.05	1.18	4.92	164.71***	− 7.41***	384
Saudi Arabia	93.11	87.79	210.64	33.18	33.35	0.76	3.47	45.30***	− 5.64***	384
South Africa	111.52	100.50	301.71	35.66	46.52	0.99	3.82	81.72***	− 2.83*	384
Thailand	94.46	85.99	296.19	35.44	38.89	1.79	7.77	631.41***	− 12.11***	384
Turkey	111.56	102.74	320.26	32.63	43.41	1.28	5.41	218.56***	− 7.29***	384
Ukraine	127.38	109.84	382.87	22.18	64.83	0.99	3.70	78.79***	− 3.39**	384
USA	85.42	66.18	545.09	23.70	63.29	3.03	16.77	4018.16***	− 7.81***	384
Venezuela	86.28	81.92	233.48	16.38	38.83	0.90	4.29	86.85***	− 4.16***	384

Table shows the descriptive statistics of the GPR series (level) for emerging economies and the USA. Mean, Median, Max, Min, SD, Skew, and Kurt denote the monthly average, median, maximum, minimum, standard deviation, skewness, and kurtosis, respectively. J.B. stands for Jarque–Bera test statistics for normality. ADF is the empirical statistic for the Augmented Dickey and Fuller (1979) test

The significance of test statistics for J.B. and ADF is denoted by *, **, and *** at 10, 5, and 1% levels, respectively

Table 2 Descriptive statistics of GPR spillovers' determinants

	Mean	Median	Max	Min	SD	Skew	Kurt	J.B.	Sample size
Pairwise Spillover (%)	5.26	1.68	10.54	0.02	12.82	4.00	18.00	4348.23***	342
Imports (USD)	5,006,500.00	763,512.60	220,000,000.00	13.87	17,401,686.00	8.67	92.08	117,369.33***	342
Exports (USD)	4,378,468.00	582,086.50	168,000,000.00	50.48	15,488,057.00	8.29	80.46	89,422.52***	342
Distance (KM)	8,832.10	8,424.24	19,772.34	55.31	5,231.83	0.18	2.07	14.84***	342
Budget deficit (% of GDP)	(0.96)	(1.91)	3.15	(6.29)	2.88	0.12	1.82	18.30***	342
Debt (% of GDP)	47.10	43.20	119.14	18.14	23.78	1.60	6.00	228.81***	342
Area (Sq. KM)	3,195,143.00	1,213,090.00	16,380,585.00	21,640.00	4,292,222.00	1.79	5.33	275.40***	342
Market capitalization (% of GDP)	61.47	52.84	194.29	9.17	45.91	1.59	4.95	209.13***	342
Dummy variables	Cases with zero	Cases with one							
Contiguous	315.00	27.00							342
Colony	298.00	44.00							342
Common language	308.00	34.00							342

Table shows the descriptive statistics of the determinants of GPR spillovers. Mean, Median, Max, Min, SD, Skew, and Kurt denote the monthly average, median, maximum, minimum, standard deviation, skewness, and kurtosis, respectively. J.B. stands for Jarque–Bera test statistics for normality

The significance of test statistics for J.B. is denoted by *, **, and *** at 10, 5, and 1% levels, respectively

Before we proceed to the formal analysis, we present the descriptive statistics of the GPR series and the underlying determinants in Tables 1 and 2, respectively. From Table 1, the skewness and kurtosis values indicate that most of the GPR indices are negatively (positively) skewed and fat-tailed. Moreover, the Augmented Dicky Fuller (1979) unit roots test results suggest that all the GPR series are stationary at a level. In contrast, the Jarque–Bera test statistics indicate that all the GPR index series are generally not distributed. Similarly, Table 2 shows that most of the variables are skewed, fat-tailed, and not normally distributed. Thus, to achieve normality, we use log forms of explanatory variables where appropriate.

2.2 *GPR Transmissions using Diebold and Yilmaz (2012)*

As our principal analysis, we apply the spillover model of Diebold and Yilmaz (2012) to measure total and pairwise GPR transmissions among our sample countries. This model is widely used in studies involving news-based indicators mainly because of the simplicity and efficiency of its estimates (see, e.g., Yin and Han 2014; Klößner and Sekkel 2014; Balli et al. 2017; Thiem 2018; Liow et al. 2018; Kang and Yoon 2019). The spillover model allows for spillover effects across various variables as the variance decomposition results do not depend on the variables' sequence. Therefore, these measures capture GPR spillovers from one country to multiple countries and vice versa. With a rich statistical approach that accommodates several country-based GPR indicators across continents, the spillover model also overcomes the limitations of Huff and Lutz's (1974) work.

The generalized spillover index of Diebold and Yilmaz (2012) let us define spillovers as the fractions of the H-step-ahead error variances in forecasting x_i that is due to shocks to x_j ($i \neq j$) for $i, j = 1, 2, \ldots, N$, where x_i and x_j represent the rates of change of GPR series i and j, respectively, and N is the total number of GPR series (19 in our case). They measure spillovers in a generalized VAR framework.[6]

Consider a covariance stationary N q-variable VAR (p), $x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t$, where x_i is the $N \times 1$ vector of the endogenous variables and $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation is written as $x_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, where the $N \times N$ coefficient matrices A_j obey a recursion of the form $A_j = \sum_{j=1}^{p} \phi_j A_{j-p}$, with A_0 being an $N \times N$ identity matrix and $A_j = 0$ for $j < 0$.

The spillovers can be defined by generalized forecast error variance decompositions of the VAR model's moving average representation. The H-step-ahead generalized forecast error variance decomposition can be written as follows:

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[6] In simple VAR framework, the results of variance decomposition and therefore spillovers are driven by Cholesky factor orthogonalization and are potentially order dependent. However, the spillover measures based on a generalized VAR framework, the results are not order dependent. For more details, see Koop et al. (1996) and Pesaran and Shin (1998).

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i \right)}, \tag{1}$$

where Σ is the variance matrix of the vector of errors ε, σ_{jj} is the standard deviation of the error term of the jth equation, and e_i and e_j are selection vector with a value of one for the ith and jth elements, respectively, and zero otherwise. A_h stands for $N \times N$ matrix of moving average coefficients corresponding to lag h.

Since own- and cross-variable variance contribution shares do not sum to one under the generalized decomposition, each entry of the variance decomposition matrix is normalized by its row sum as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{2}$$

By construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.
Thus, a total spillover (*TS*) index can be defined as

$$\text{TS}(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100. \tag{3}$$

This index measures the average contribution of spillovers from shocks to all (other) GPRs to the total forecast error variance. Similarly, the directional spillovers (DS) transmitted by the GPR of country i to the GPR of country j can be measured by:

$$\text{DS}_{i \to j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100. \tag{4}$$

The results of total and pairwise GPR transmissions are shown in Table 3.

2.3 *Short- and Long-term GPR transmissions using* Baruník and Křehlík (2018)

This section lays out details of the spillover framework recently introduced by Baruník and Křehlík (2018), which allows us to explore the short- and long-term aspects of GPR transmission. Notably, when spillovers across a set of variables are quantified using the Diebold and Yilmaz (2012) model, the shocks are aggregated without considering their responsiveness at different frequencies, i.e., short- versus long-term time horizons. Thus, the model completely ignores the possibility of heterogeneous frequency responses to shocks. However, in many economic, social, and geopolitical phenomena, including GPR, it may be interesting to assess short- and long-term transmission of shocks rather than the transmission seen at a single frequency band. Hence, the GPR transmission results may differ depending upon the frequency band at which they are computed. This may invite a further investigation into our results calculated from the spillover model of Diebold and Yilmaz (2012).

Table 3 Total directional spillovers of GPR

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
Argentina	55.93	9.16	1.35	4.15	1.57	0.70	0.73	1.76	1.23	3.21	0.44	1.44	2.19	6.43	0.09	1.29	1.10	3.44	3.81	44.07
Brazil	9.45	49.64	3.61	3.66	2.38	1.40	0.78	4.92	2.46	5.10	0.82	1.62	2.89	2.22	0.44	2.20	0.28	3.01	3.12	50.36
China	1.35	4.35	47.38	0.63	5.55	0.19	1.58	8.55	1.99	4.69	1.85	7.32	2.47	0.54	1.96	2.85	0.32	6.40	0.04	52.62
Colombia	3.84	6.14	0.55	72.75	1.45	0.34	0.15	0.20	0.20	4.46	0.91	0.78	1.04	0.53	0.16	0.32	0.13	0.94	5.11	27.25
India	0.54	1.96	5.67	0.47	63.23	1.29	2.62	0.20	1.79	2.19	2.24	4.69	1.80	1.06	1.64	0.85	0.02	6.77	1.00	36.77
Indonesia	1.07	1.75	0.18	0.57	2.68	62.43	0.45	0.94	9.72	1.52	2.89	0.76	0.72	0.49	6.30	0.46	1.39	1.40	4.25	37.57
Israel	0.91	0.97	1.46	0.23	2.61	0.29	59.31	0.36	0.73	1.33	0.76	5.23	8.09	0.69	0.07	6.48	1.01	8.86	0.60	40.69
Korea	1.92	5.78	10.54	0.18	0.18	0.88	0.35	66.36	1.69	2.16	0.94	1.29	0.26	3.09	1.90	0.15	1.01	1.07	0.24	33.64
Malaysia	1.03	2.94	2.19	0.34	2.14	8.87	0.69	2.03	57.97	1.98	3.95	1.17	2.44	1.24	5.32	0.86	0.29	3.59	0.96	42.03
Mexico	3.11	4.48	4.78	3.10	2.69	1.59	0.95	2.03	1.78	56.20	1.22	3.07	2.79	0.96	2.20	2.71	0.53	3.04	2.75	43.80
Philippines	0.81	1.15	2.19	1.14	2.24	3.82	0.78	1.48	3.06	1.41	67.20	0.83	0.70	2.56	6.52	0.49	0.03	3.02	0.57	32.80
Russia	1.09	1.34	7.79	0.59	5.54	0.83	3.50	1.01	1.13	2.36	0.24	51.17	3.14	0.28	1.29	4.20	5.78	7.73	1.00	48.83
Saudi Arabia	1.90	3.26	2.83	0.62	2.51	0.43	8.66	0.80	2.10	4.19	0.30	4.53	50.38	0.57	0.11	6.57	0.04	8.82	1.40	49.62
South Africa	6.02	2.81	0.56	0.09	1.84	0.06	0.97	4.01	0.53	1.40	2.92	0.46	1.71	71.65	0.60	0.44	1.51	1.63	0.79	28.35
Thailand	0.13	0.58	3.02	0.42	2.26	6.14	0.21	1.87	7.05	2.36	6.08	1.19	0.54	0.71	66.41	0.27	0.26	0.41	0.10	33.59
Turkey	1.15	2.07	2.99	0.07	0.76	0.53	5.36	0.44	0.98	2.53	0.12	5.50	7.04	0.83	0.54	61.16	0.61	7.22	0.12	38.84
Ukraine	0.78	0.68	0.71	0.73	0.88	1.05	1.53	0.82	0.31	0.80	0.13	8.49	0.46	1.70	0.42	0.82	78.35	0.26	1.10	21.65
United States	2.86	2.82	6.16	0.47	5.41	1.25	6.56	0.92	3.11	2.79	2.16	7.34	7.47	1.00	0.47	5.45	0.11	42.71	0.93	57.29

Table 3 (continued)

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
Venezuela	5.09	3.69	0.06	4.36	1.80	3.74	0.32	0.69	1.37	4.05	0.61	0.08	1.96	0.68	0.28	0.04	0.31	1.29	69.60	30.40
To others	43.07	55.93	56.61	21.80	44.48	33.39	36.20	33.02	41.22	48.50	28.59	55.77	47.73	25.57	30.33	36.43	14.75	68.92	27.88	**39.48%**

The spillover model of Diebold and Yilmaz (2012) has been used to calculate these GPR spillovers, without considering any frequency bands. The sample is from January 1985 through December 2016, and the predictive horizon is 100 months. The ijth entry of the upper-left 19×19 country submatrix gives the ijth pairwise directional spillover; i.e., the percent of 100-month-ahead forecast error variance in GPR of country i due to shocks from GPR in country j. The rightmost (From Others) column gives total directional spillover (from); i.e., row sums (from all others to i). The bottom (to others) row gives total directional spillover (to); i.e., column sums (to all others from j). The bottom-right element (in boldface) is total spillover (mean "from" spillover, or equivalently, mean "to" spillover)

It might, therefore, seem more appropriate to work with frequency bands. The connectedness framework of Baruník and Křehlík (2018) can be used to perform this task.

Within this framework, the term connectedness is simply another name for transmissions or spillovers. By introducing the spectral representation of variance decomposition (e.g., Stiassny 1996; Dew-Becker and Giglio 2016), this approach expands Diebold and Yilmaz (2012). The unique feature of the Barunik–Krehlik approach is its potential to capture the transmission among a set of variables (over time and) across different frequencies.

In Diebold and Yilmaz (2012), generalized forecast error variance decompositions are central to ascertaining the transmissions in the time domain. Similarly, it becomes crucial to use a spectral representation of the variance decomposition based on frequency responses to estimate transmissions in the frequency domain. In this case, spectral decomposition methods are employed to capture the transmission relationships within the frequency domain; this is achieved by using the approaches introduced by Stiassny (1996) and Dew-Becker and Giglio (2016). The frequency response function plays a central role in this framework, which can be obtained as the Fourier transform of the coefficients A_h, with $i = \sqrt{-1}$, can be defined as:

$$A\left(e^{-ih\omega}\right) = \sum_{h=0}^{\infty} e^{-ih\omega} A_h \tag{5}$$

where ω denotes the frequency, for example, short and long term.

As a next step, the power spectrum $S_x(\omega)$, which indicates how the variance of x_t is distributed over the frequency components ω, is computed as:

$$S_x(\omega) = \sum_{h=0}^{\infty} E\left(x_t x_{t-h}\right) e^{-ih\omega} = A\left(e^{-ih\omega}\right) \sum A\left(e^{ih\omega}\right) \tag{6}$$

According to Baruník and Křehlík (2018), the frequency response functions can be used to obtain the generalized variance decompositions in the frequency domain. Specifically, the generalized forecast error variance decompositions at a specific frequency ω is calculated as:

$$\theta_{ij}(\omega) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} \left(A\left(e^{-ih\omega}\right)\Sigma\right)_{ij}^2}{\sum_{h=0}^{\infty} \left(A\left(e^{-ih\omega}\right) \sum A\left(e^{ih\omega}\right)\right)_{ii}}, \tag{7}$$

where at a given frequency ω, $\theta_{ij}(\omega)$ denotes the share of the spectrum of the variable i that can be attributed to shocks in the variable j. The forecast horizon H does not play much role in this context.

For time-domain analysis, Eq. (7) can be normalized as:

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{h=1}^{n} \theta_{ij}(\omega)}. \tag{8}$$

Importantly, $\tilde{\theta}_{ij}(\omega)$ measures pairwise connectedness from i to j at a given frequency ω and, therefore, it can be interpreted as a within-frequency causality indicator. In contrast, the above-mentioned $\tilde{\theta}_{ij}(H)$ reflects pairwise connectedness from i to j at a particular horizon H. It can be viewed as an indicator of the strength of causality exclusively in the same domain. In this regard, when Diebold and Yilmaz (2012) quantify connectedness using $\tilde{\theta}_{ij}(H)$, they focus on information aggregated through frequencies, while the possible heterogeneous frequency response to shocks is ignored.

In economic and financial applications, it can be interesting to assess short-, medium-, or long-term transmission rather than transmission at a single frequency. Hence, it seems more appropriate to work with frequency bands. In this setting, the accumulative transmission at an arbitrary frequency band $d = (a, b)$ can be obtained as:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega) \, \mathrm{d}\omega. \tag{9}$$

From here, it is possible to define a variety of transmission measures in the frequency domain, which are inspired by the indicators introduced by Diebold and Yilmaz (2012) for the time domain. For example, the overall or system-wide transmission within the frequency band d can be calculated as:

$$C^d = \frac{\sum_{i=1, i \neq j}^n \tilde{\theta}_{ij}(d)}{\sum_{ij} \tilde{\theta}_{ij}(d)} = 1 - \frac{\sum_{i=1}^n \tilde{\theta}_{ii}(d)}{\sum_{ij} \tilde{\theta}_{ii}(d)}. \tag{10}$$

Note that C^d close to unity implies strong transmission within the frequency band d. However, the weight of this spectral band within the aggregate transmission might be meager. Hence, these measures are called within measures as they describe only the transmission within a particular frequency band.

According to Baruník and Křehlík (2018), the within measures have to be weighted to get an indicator of a given frequency band's contribution to aggregate transmission. Thus, the contribution of the frequency band d to the overall or system-wide transmission can be obtained as:

$$\tilde{C}^d = C^d \cdot \Gamma(d) \tag{11}$$

where the spectral weight $\Gamma(d) = \sum_{ij=1}^n \tilde{\theta}_{ij}(d) / \sum_{i=1}^n \tilde{\theta}_{ij} = \sum_{ij=1}^n \tilde{\theta}_{ij}(d)/n$ reflects the contribution of the frequency band d to the whole VAR system, while C^d is the total transmission measure corresponding to the spectral band d computed according to Eq. (10). Lastly, it should be mentioned that the sum of all frequency transmission measures over disjointed intervals is equal to the original total transmission measure proposed by Diebold and Yilmaz (2012), i.e., $C = \sum_d \tilde{C}^d$.

The short- and long-term GPR transmission results obtained through Baruník and Křehlík (2018) are given in Tables 4 and 5, respectively.

2.4 Pictorial description

Figures 1, 2, and 3 provide pictorial descriptions of the results shown in Tables 3, 4, and 5, respectively. These figures have been created with the aid of Gephi (https://gephi.github.io/), open-source, highly interactive, and user-friendly software that allows for discovering and visualizing network patterns among data.

2.5 Cross-sectional determinants

Once we compute the pairwise GPR transmissions, the next step is to explain them. We now invoke the gravity model for this purpose. The gravity model was initially developed to understand international migration flows. Vanderkamp (1977) has recently successfully explained the cross-country transmission of conflict and information. The gravity model's underlying concept is that the flow of goods and people between two destinations is directly proportional to their respective economic masses (or income levels) and inversely proportional to the distance between them (Morley et al. 2014). Studies that have used the gravity model framework for explaining the spread of conflict typically built on an analogy between infectious disease and the spread of a conflict (Blomberg and Rosendorff 2006; Braithwaite 2010; Buhaug and Gleditsch 2008). This analogy suggests that the spread of conflict varies with the degree of interaction between interacting units (typically countries). The gravity model framework captures this dyadic interaction between countries by involving each country's size and geographical distance. Assuming the same set of factors shape the information transmission (in our case, GPR transmission) associated with a conflict, we expect closer countries to experience a higher transmission level than distant ones.

The meaning of size and distance may differ depending upon the context in which they are used in a gravity model (Fidrmuc and Karaja 2013). The distance may be interpreted as how distant, or close two countries are in terms of their bilateral linkages such as geographical proximity, cultural and historical similarity, or economic ties. Size may also refer to a given country's economic, geographic, or public (population) mass.

We measure economic distance through bilateral trade; the magnitude of bilateral trade captures how distant or close the countries are in economic terms. There is mixed evidence on the role of bilateral trade in the spread or eruption of geopolitical conflicts (see Barbieri (1996), for a summary of the debate). Most studies support trade's pacific benefit; bilateral trade promotes peace or reduces conflict between states (Hegre et al. 2010). Others find that trade does not deter conflict (Keshk et al. 2004; Kim and Rousseau 2005). Some also argue that higher trade or extensive economic interdependence increases interstate conflict likelihood (Barbieri 1996; Waltz 1979). Many consider trade as irrelevant or less critical to interstate conflicts (Blanchard and Ripsman 1994; Buzan 1984; Levy 1989).

In our case, however, it is not the physical conflict that we are trying to explain. We aim to see whether the pairwise GPR transmission occurring in transnational information flows is affected by bilateral trade. Following the above literature on

Table 4 Short-term directional spillovers of GPR

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
Argentina	47.34	7.29	1.11	3.75	1.55	0.53	0.55	1.48	0.95	2.68	0.36	1.32	1.75	5.83	0.08	1.14	1.05	2.68	3.04	37.14
Brazil	8.07	41.35	3.16	2.82	2.23	1.28	0.49	4.44	2.06	4.48	0.62	1.46	2.30	1.89	0.37	1.99	0.26	2.20	2.66	42.79
China	1.16	3.97	38.61	0.61	4.97	0.16	1.46	7.24	1.67	4.15	1.58	6.11	2.07	0.51	1.23	2.50	0.18	5.22	0.04	44.84
Colombia	3.29	5.54	0.51	64.17	1.43	0.31	0.13	0.19	0.18	3.95	0.75	0.76	0.94	0.52	0.15	0.30	0.13	0.87	4.52	24.48
India	0.36	1.52	4.39	0.32	51.78	0.87	2.25	0.18	1.21	1.72	1.61	3.41	1.16	0.74	1.21	0.76	0.02	4.93	0.64	27.29
Indonesia	0.80	1.25	0.13	0.44	2.60	53.85	0.41	0.77	8.45	1.18	2.40	0.74	0.50	0.49	5.80	0.42	1.19	0.97	3.23	31.77
Israel	0.64	0.83	1.18	0.22	2.33	0.22	48.62	0.29	0.53	1.18	0.63	4.62	6.14	0.55	0.04	5.68	0.74	7.08	0.48	33.36
Korea	1.41	4.93	8.47	0.17	0.15	0.65	0.27	55.31	1.31	1.81	0.65	0.90	0.19	2.50	1.22	0.09	0.97	0.72	0.15	26.55
Malaysia	0.94	2.51	1.76	0.34	2.08	7.46	0.52	1.86	48.62	1.55	3.63	0.97	1.75	1.22	4.68	0.72	0.29	2.59	0.71	35.55
Mexico	2.58	3.45	4.19	2.53	2.51	1.43	0.64	1.86	1.38	48.03	0.89	2.70	2.11	0.78	1.90	2.40	0.41	2.30	2.23	36.26
Philippines	0.75	0.92	1.71	0.96	1.80	3.30	0.55	1.39	2.27	1.04	56.04	0.64	0.49	2.14	5.52	0.40	0.02	2.26	0.38	26.53
Russia	0.68	1.03	6.56	0.46	5.11	0.68	2.59	0.77	0.74	1.61	0.15	42.36	2.30	0.25	0.85	3.18	4.77	5.41	0.90	38.04
Saudi Arabia	1.48	2.77	2.51	0.49	2.42	0.31	7.80	0.79	1.72	3.90	0.27	4.20	42.76	0.44	0.09	5.66	0.03	7.43	1.04	43.36
South Africa	4.71	2.15	0.51	0.07	1.79	0.05	0.69	3.61	0.47	1.22	2.55	0.41	1.31	60.09	0.55	0.42	1.39	1.37	0.68	23.92
Thailand	0.09	0.35	2.72	0.42	2.02	5.44	0.19	1.69	6.40	1.74	4.88	0.95	0.54	0.45	54.48	0.26	0.15	0.33	0.08	28.70
Turkey	0.78	1.39	2.03	0.06	0.51	0.47	4.03	0.34	0.61	1.82	0.07	4.48	5.31	0.81	0.44	49.95	0.49	4.88	0.11	28.64
Ukraine	0.57	0.51	0.68	0.68	0.84	1.04	1.23	0.55	0.28	0.60	0.10	6.87	0.45	1.57	0.27	0.66	65.11	0.22	1.09	18.20

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Table 4 (continued)

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
USA	2.01	2.08	4.99	0.33	4.51	0.80	4.91	0.80	2.05	2.18	1.51	5.77	5.32	0.74	0.33	4.10	0.08	32.50	0.57	43.09
Venezuela	4.21	2.70	0.06	3.21	1.72	2.89	0.31	0.67	1.03	3.49	0.48	0.07	1.57	0.55	0.25	0.04	0.29	1.00	58.28	24.55
To others	34.55	45.18	46.65	17.88	40.55	27.89	29.02	28.91	33.30	40.29	23.11	46.39	36.19	21.99	24.98	30.72	12.46	52.44	22.55	**32.37%**

The spillover model of Baruník and Křehlík (2018) has been used to calculate these short-term GPR spillovers. The short-term spillovers correspond to frequency band of less than 3 months. The sample is from January 1985 through December 2016, and the predictive horizon is 100 months. The ijth entry of the upper-left 19 × 19 country submatrix gives the ijth pairwise directional spillover; i.e., the percent of 100-month-ahead forecast error variance in GPR of country i due to shocks from GPR in country j. The rightmost (from others) column gives total directional spillover (from); i.e., row sums (from all others to i). The bottom (to others) row gives total directional spillover (to); i.e., column sums (to all others from j). The bottom-right element (in boldface) is total spillover (mean "from" spillover, or equivalently, mean "to" spillover)

the role of international trade in interstate conflicts (Barbieri 1996; Hegre et al. 2010, for instance), we argue that bilateral trade is likely to increase the GPR transmission between the two countries. Our argument is based on the cross-border concerns that prevail among the public, businesses, and governments when two countries trade more. People immediately become concerned about geopolitical events or conflicts in countries where they or their governments have economic interests. Because of strong trade ties between the two countries, a hike in foreign GPR would cause concerns in the local public and increase GPR in the home country. In other words, GPR will transmit across trading partners because of underlying concerns (Kuran 1998) that emerge from the recognition of mutual benefits of bilateral trade. Therefore, other things equal, we would expect a positive association between bilateral trade and pairwise GPR transmission. In addition, bilateral trade may foster a learning mechanism. Trade improves interstate linkages and removes communication barriers, facilitating information flows and enabling learning. This social learning mechanism may stimulate the local public to emulate foreign geopolitical conflict in the home country (Hill and Rothchild 1986; Hill et al. 1998). In this way, it will facilitate GPR transmission.

In our model, contiguity (or border sharing) and bilateral distance represent the extent of geographical distance (or proximity) between two countries. Both the factors have been previously included in the models that explain the spread of conflicts beyond state boundaries. For instance, Buhaug and Gleditsch (2008) find that proximity to a conflict explains the spillover effect on a domestic conflict onset probability. Similarly, Hegre et al. (2010) find that while contiguity tends to increase the spread of conflict, distance has an opposite effect. That is, the extent of proximity explains the scale of conflict spread.

Moreover, Blomberg and Rosendorff (2006) show that distance and border significantly explain transnational terrorism flows. Because of their importance, previous research has suggested that the contiguity and the distance between two states' capitals should be used in analyses of interstate violence (Oneal and Russett 1999). The reasons are straightforward. States that share a border are particularly prone to conflict, and non-contiguous states in the same region are more likely to fight than more remote pairs. Also, a dichotomous indicator of contiguity is not highly correlated with distance. Following this literature, we also include border sharing and distance in our model. Accordingly, we would expect contiguity to increase and distance to decrease the pairwise GPR transmission. Contiguity and distance were also included in the information transmission models of Fidrmuc and Karaja (2013) and Balli et al. (2017)

Common language, colony, and common colony are used to capture countries' cultural and historical distance. The fear or concern (Kuran 1998) and emulation through social learning (Hill and Rothchild 1986; Hill et al. 1998) may be invoked. Accordingly, one may argue that linguistic and historical ties contribute to concern and learning, thus facilitating transmission. This argument is indeed plausible since Blomberg and Rosendorff (2006) found common language's role in transmitting terrorism across countries. Thus, we expect a positive association between pairwise GPR transmission and cultural and historical distance between them.

Table 5 Long-term directional spillovers of GPR

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
Argentina	8.59	1.87	0.24	0.39	0.02	0.17	0.18	0.28	0.28	0.53	0.08	0.12	0.44	0.59	0.01	0.15	0.05	0.76	0.77	6.93
Brazil	1.39	8.28	0.45	0.84	0.16	0.12	0.29	0.48	0.40	0.62	0.20	0.16	0.59	0.34	0.07	0.21	0.01	0.81	0.45	7.57
China	0.19	0.38	8.77	0.02	0.58	0.03	0.12	1.31	0.31	0.54	0.26	1.21	0.40	0.03	0.73	0.34	0.14	1.18	0.00	7.78
Colombia	0.55	0.60	0.05	8.59	0.02	0.03	0.03	0.01	0.02	0.50	0.16	0.02	0.10	0.00	0.00	0.01	0.00	0.07	0.58	2.76
India	0.18	0.44	1.27	0.15	11.45	0.42	0.37	0.02	0.58	0.47	0.63	1.27	0.64	0.32	0.43	0.09	0.00	1.84	0.36	9.49
Indonesia	0.27	0.50	0.05	0.13	0.09	8.58	0.04	0.17	1.27	0.34	0.49	0.01	0.22	0.00	0.51	0.04	0.21	0.44	1.02	5.80
Israel	0.26	0.14	0.28	0.01	0.28	0.07	10.68	0.07	0.21	0.15	0.14	0.61	1.95	0.14	0.03	0.80	0.26	1.78	0.12	7.33
Korea	0.51	0.85	2.07	0.01	0.03	0.23	0.08	11.05	0.37	0.35	0.29	0.39	0.08	0.59	0.69	0.06	0.04	0.36	0.08	7.08
Malaysia	0.09	0.44	0.43	0.00	0.06	1.41	0.17	0.17	9.35	0.43	0.33	0.20	0.69	0.02	0.64	0.13	0.00	1.01	0.25	6.48
Mexico	0.53	1.03	0.60	0.58	0.19	0.16	0.32	0.17	0.40	8.17	0.33	0.37	0.69	0.18	0.29	0.31	0.12	0.74	0.52	7.54
Philippines	0.06	0.23	0.48	0.17	0.44	0.52	0.23	0.09	0.79	0.37	11.15	0.19	0.21	0.43	1.01	0.09	0.01	0.77	0.18	6.27
Russia	0.41	0.31	1.23	0.13	0.42	0.15	0.90	0.24	0.39	0.75	0.10	8.81	0.83	0.02	0.43	1.03	1.01	2.32	0.10	10.80
Saudi Arabia	0.42	0.49	0.32	0.13	0.10	0.12	0.86	0.01	0.38	0.29	0.02	0.33	7.62	0.12	0.02	0.91	0.00	1.39	0.36	6.26
South Africa	1.31	0.66	0.05	0.02	0.05	0.01	0.29	0.40	0.06	0.18	0.37	0.05	0.40	11.56	0.05	0.03	0.12	0.26	0.11	4.43
Thailand	0.04	0.23	0.30	0.00	0.24	0.71	0.02	0.17	0.65	0.62	1.21	0.24	0.00	0.26	11.93	0.00	0.11	0.08	0.02	4.89
Turkey	0.37	0.68	0.96	0.00	0.25	0.06	1.33	0.10	0.37	0.71	0.05	1.01	1.74	0.02	0.11	11.21	0.13	2.34	0.01	10.21
Ukraine	0.21	0.17	0.03	0.05	0.04	0.01	0.29	0.26	0.03	0.20	0.03	1.62	0.00	0.13	0.15	0.16	13.24	0.04	0.01	3.44
USA	0.85	0.74	1.16	0.14	0.90	0.45	1.65	0.12	1.06	0.60	0.65	1.57	2.15	0.26	0.14	1.35	0.03	10.22	0.36	14.19

Table 5 (continued)

	Argentina	Brazil	China	Colombia	India	Indonesia	Israel	Korea	Malaysia	Mexico	Philippines	Russia	Saudi Arabia	South Africa	Thailand	Turkey	Ukraine	USA	Venezuela	From others
Venezuela	0.88	0.98	0.00	1.14	0.08	0.85	0.01	0.01	0.33	0.56	0.13	0.01	0.39	0.12	0.04	0.00	0.03	0.30	11.32	5.86
To others	8.52	10.75	9.96	3.92	3.93	5.51	7.18	4.11	7.91	8.20	5.48	9.38	11.53	3.58	5.35	5.71	2.29	16.48	5.32	**7.11%**

The spillover model of Baruník and Křehlík ([2018](#)) has been used to calculate these long-term GPR spillovers. The long-term spillovers correspond to frequency band between 3 and 100 months. The sample is from January 1985 through December 2016, and the predictive horizon is 100 months. The ijth entry of the upper-left 19×19 country submatrix gives the ijth pairwise directional spillover; i.e., the percent of 100-month-ahead forecast error variance in GPR of country i due to shocks from GPR in country j. The rightmost (from others) column gives total directional spillover (from); i.e., row sums (from all others to i). The bottom (to others) row gives total directional spillover (to); i.e., column sums (to all others from j). The bottom-right element (in boldface) is total spillover (mean "from" spillover, or equivalently, mean "to" spillover)

Large countries can project their power at a great distance and engage several countries at once. They have more neighbors and far-reaching economic and political interests. Thus, a nation's size indicates both opportunity and willingness to involve in a conflict. Literature shows that, like proximity, countries' sizes influence the likelihood of interstate conflicts (Bearce and Fisher 2002; Hegre 2008; Kenneth 1962; Werner 1999; Xiang et al. 2007). In this literature, GDP per capita or just GDP, population size, and geographical area are orthodox candidates for country size (Braithwaite 2010; Buhaug and Gleditsch 2008; Hegre et al. 2010). However, we include only two considering their relevance. The geographical area is included because GPR is intrinsically a geographic attribute of conflict, and therefore is vital to our study. Following Blomberg and Rosendorff (2006), we include each country's geographical area in our model. To represent the economic size, we use each country's stock market capitalization in the pair. This is because we measure the information transmission of GPR, and studies have shown that stock market capitalization is more relevant when it comes to such information transmission processes (i.e., Balli et al. 2017). Economic size may also be interpreted as state capacity to deal with problematic issues as larger economies generally have more resources to tackled problems. Studies suggest that state capacity diminishes the likelihood of new conflict (Braithwaite 2010), implying a negative association between GPR transmission and economic size. Following Braithwaite (2010), we would expect a negative association between economic size and GPR transmission. On the other hand, we expect a positive link between the geographical area and GPR spillover.

Finally, some studies have also associated conflict spread to a so-called "bad neighborhood" effect (Iqbal and Starr 2008). These studies typically argue that the state undergoing a range of economic, social, and political problems is likely contagious for their neighboring states. Countries experiencing economic problems often do poorly at managing fiscal balance and foreign debt. Balli et al. (2017) find that the countries' fiscal imbalances and financial liabilities are responsible for cross-country information spillovers associated with economic policy uncertainties. Combining these two notions, one may argue that each country's fiscal imbalance and foreign debt increase the pairwise GPR transmission. This is why we add the central government's debt and fiscal imbalance (budget deficit) in our model.

We estimate the following cross-sectional equation in order to test the relationships discussed in the previous section[7]:

$$
\begin{aligned}
DS_{ij} = &\alpha_o + \alpha_1 Log(Exports_{ij} + Imports_{ij}) \\
&+ \alpha_2 Contiguous_{ij} + \alpha_3 Colony_{ij} \\
&+ \alpha_4 Common\ Colony_{ij} + \alpha_5 Common\ Language_{ij} \\
&+ \alpha_6 Log(Distance_{ij}) + \beta * X_{i\ and\ j} + \in_{ij}
\end{aligned}
\tag{12}
$$

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[7] Some of these factors such as common language and geographical proximity were also suggested by the Emerging Risk Report (2016), produced by LLOYD'S, in their "framework for understanding the emergence and spread of civil unrest."
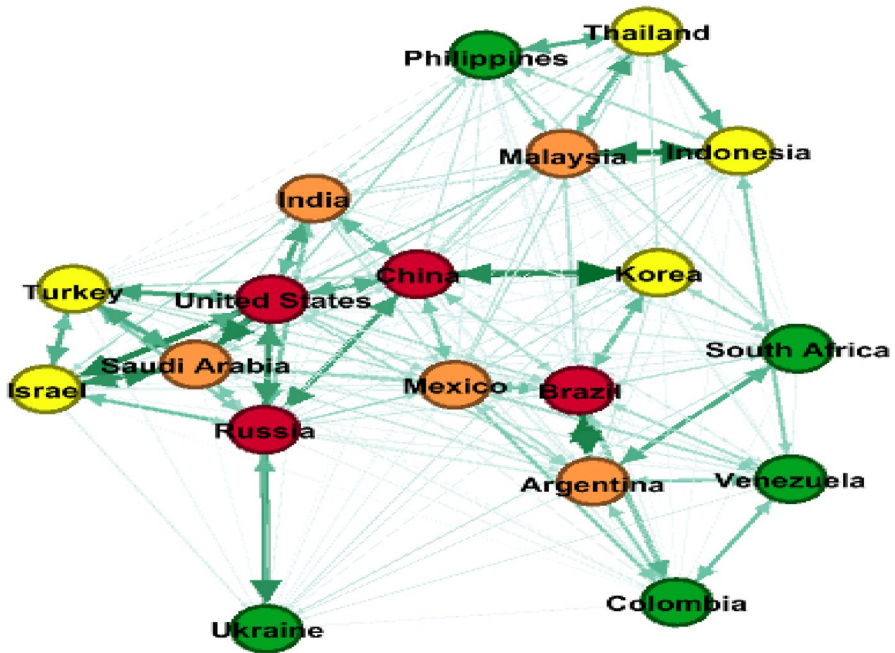
Fig. 1 Total pairwise directional spillovers of GPR (Spring Graph). The Spring Graph presented in figure shows the total pairwise (static) GPR spillovers among sample countries presented in Table 3. The colors of nodes (circles) are in the following order: green (25th percentile), yellow (50th percentile), orange (75th percentile), and red (> 75th percentile). There are two aspects to the pairwise "To Others" spillovers, i.e., the width and the shade of the arrow. The wider and darker arrow represents higher pairwise "To Others" spillovers (color figure online)

where DS_{ij} represents the amount of GPR spillover from $Country_i$ to $Country_j$. The overall regressions will be using the model output from Diebold and Yilmaz (2012); for the short- and long-term regressions, it will be the Baruník and Křehlík (2018) model. $Log(Exports_{ij} + Imports_{ij})$ is an indicator for bilateral trade between country i and country j. $Contigous_{ij}$ is a dummy variable equal to 1 if the two countries share a border. $Colony_{ij}$ and $CommonColony_{ij}$ are dummies indicating colonial dependence and whether both countries have remained under the same colonial power. $CommonLanguage_{ij}$ is a dummy variable for common language and $Log(Distance_{ij})$ is the logarithm of the distance between the capital cities of two countries. X_{iandj} contains country-specific factors, namely budget deficit, central government debt, geographical area, and stock market capitalization of each country.
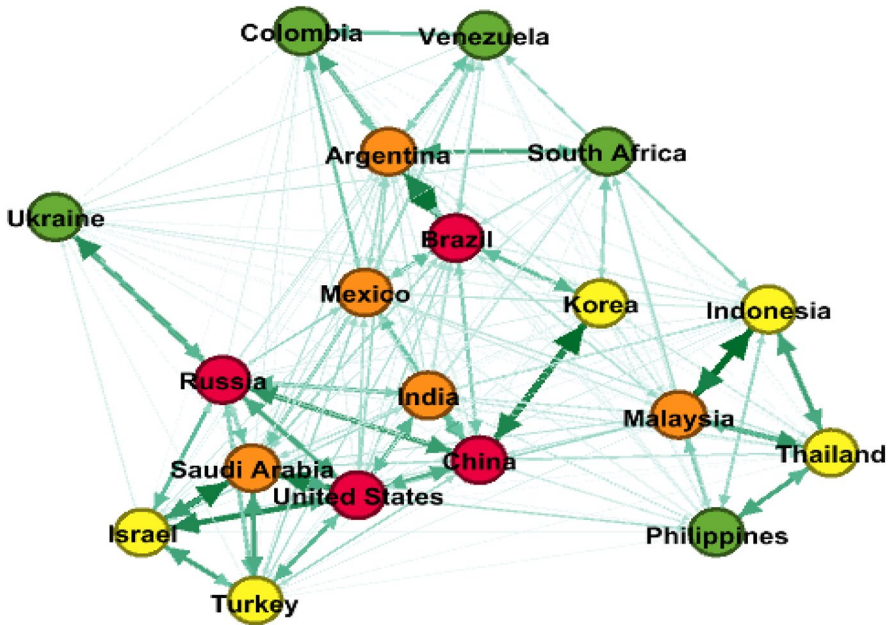
Fig. 2 Short-term pairwise directional spillovers of GPR (Spring Graph). The Spring Graph presented in figure shows the pairwise (static) short-term GPR spillovers among sample countries presented in Table 4. The colors of nodes (circles) are in the following order: green (25th percentile), yellow (50th percentile), orange (75th percentile) and red (> 75th percentile). There are two aspects to the pairwise "To Others" spillovers, i.e., the width and the shade of the arrow. A wider and darker arrow represents higher pairwise "To Others" spillovers (color figure online)

3 Results and discussion

3.1 *Total and pairwise GPR transmission*

The results obtained by applying the spillover model of Diebold and Yilmaz (2012) are presented in Table 3. The table provides the estimates of GPR spillovers each country receives from (rows) and transmits to (columns) another country. The table also shows the total GPR spillovers each country transmits to all other countries (to others) and those each country receives from all other countries (from others). Finally, the table also includes the amounts of the total (or system-wide) mean spillovers.

Table 3 offers several key features of the GPR transmissions. First, the table indicates that the total mean spillover is about 39%. Second, in general, countries that transmit more spillovers to others are also the ones that receive more, while the amounts of transmission are slightly higher than those of reception. In particular, the USA (69), Russia (55), Brazil (56), China (57), and Saudi Arabia (48) are among the highest contributors to the forecast error variance of the remaining countries. In contrast, the USA (57), Russia (49), Brazil (50), China (53), and Saudi Arabia (50) are also the leading receivers of forecast error variance from the remaining countries.
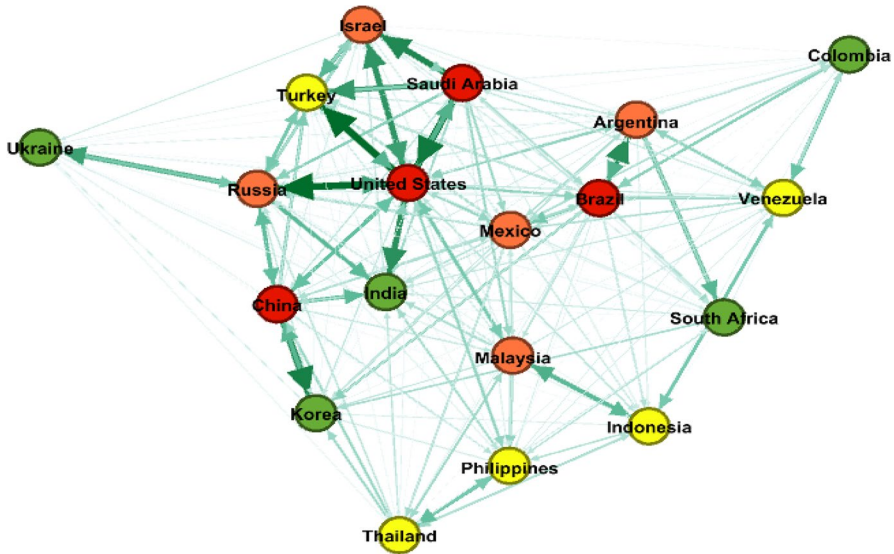
Fig. 3 Long-term pairwise directional mean spillovers of GPR (Spring Graph). The Spring Graph presented in figure shows the long-term pairwise (static) GPR spillovers among sample countries presented in Table 5. The colors of nodes (circles) are in the following order: green (25th percentile), yellow (50th percentile), orange (75th percentile), and red (>75th percentile). There are two aspects to the pairwise "To Others" spillovers, i.e., the width and the shade of the arrow. A wider and darker arrow represents higher pairwise "To Others" spillovers (color figure online)

Third, countries with larger geographical sizes are mainly responsible for the highest amount of GPR spillovers. Note that the countries listed above are also the ones with a larger geographical size. Fourth, more spillover is observed among countries situated in the same geographical region, with some exceptions. For neighboring countries (which share borders), the amount of GPR transmission is even higher. In general, the closer (farther) the countries, the higher (lower) spillover among them. Finally, trading partners have a higher magnitude of pairwise spillovers between them.

Figure 1 exhibits a pictorial description of the critical observations taken from Table 3. The figure shows a static (full-sample) network graph of mean spillovers. It is evident from the figure that most countries in the same geographical region are clustered around each other, meaning there is a higher level of GPR transmission. This is typically the case for Southeast Asia, Latin America, East Asia, Gulf, and East European Plain. However, the number of countries and the extent of intra-cluster transmission (i.e., the closeness) varies across clusters. In particular, the number of countries within a cluster range from five (Brazil, Argentina, Mexico, Colombia, and Venezuela) in Latin America to two (Russia and Ukraine) in East European

Plain and the countries in the Middle East (Israel, Turkey,[8] and Saudi Arabia) are much closer than the ones in Latin America. A country with the largest geographical size within each region is usually the leading GPR spillover participant in that region. For instance, while observing Latin America, the East European Plain, and South Asia, the leading countries, shown in "Red" nodes, are Brazil, Russia, and China, respectively. Finally, the USA is the highest participant in GPR transmission across the sample countries, as noted from its central location in the figure.

In passing, note that our GPR transmission results seem to be dictated by geographic clustering. However, it is not clear whether this clustering is explained only by geographic factors or some other bilateral and country-specific factors are also relevant here. Some countries are far from each other, yet they are tightly connected in GPR shocks. This implies that geographical linkages do not suffice to explain the heterogeneity found in our GPR transmission results.

There may be other possible determinants of this transmission. To this end, in the following section, we introduce an explanatory regression framework to dig deeper into the cross-country GPR transmissions by including certain bilateral and country-specific factors that may help to explain this transmission.

3.2 Determinants of GPR transmission

Table 4 includes the coefficient estimates for Eq. (12) of the determinants of pairwise GPR transmission, where DS_{ij}, is using the Diebold and Yilmaz (2012) model as specified in Eq. (4). Note that while $Country_i$ is the transmitter of GPR shocks, $Country_j$ is the recipient of those shocks. Column (1) of the table includes estimates of the gravity model with bilateral linkages, while column (2) shows estimates of the gravity model (extended), which incorporates country-specific variables. As motivated in methodology section, we conjecture that bilateral linkages and country-specific factors included in Eq. (12) may be possible determinants of DS_{ij}.

Columns (1) and (2) show that bilateral trade and geographical proximity (contiguity and distance) significantly explain the pairwise GPR transmission. In column (1), bilateral trade is a positive and significant (at 1%) determinant of the pairwise GPR transmission. A 1% increase in $\log(Exports_{ij} + Imports_{ij})$ increases DS_{ij} by 0.0027%. This impact increases slightly to 0.0038% in column (2) when country-specific variables are included. The coefficient of bilateral trade is very small. This may be due to the lower levels of trade volume between emerging economies relative the world trade as most trade has been between developed–developed or developed to emerging economies. Hence, the trade volume in emerging economies is at low levels; a bulk increase in the trade volume would make a big percentage change.[9] Border sharing is also a significant driver of DS_{ij}. In column (1), the

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[8] For the sake of grouping, we consider Turkey as part of Gulf region, because being a Muslim country it may be affected more by the GPRs of Israel and Saudi Arabia than other countries, except the USA, in the sample.

[9] Bilateral trade volume between Turkey and Venezuela increased by 500% in the last 6–7 years. It is because the initial level of bilateral trade was very low.

coefficient of $Contigous_{ij}$ implies that a $Country_i$ that shares a border with $Country_j$ transmits on average 1.7240% higher DS_{ij} to $Country_j$ than to a comparable country that does not share a border (significant at 1%). Once country-specific variables are included (column 2), this coefficient reduces slightly to 1.5410% (significant at 5%). The distance between 2 countries is negatively associated with DS_{ij}. A 1% increase in log($Distance_{ij}$) decreases DS_{ij} by 0.0082% in column (1) and by 0.0050% in column (2), (significant at 1% for both).

These findings suggest that the extent of economic distance (bilateral trade) and geographical proximity (geographical distance and border sharing) determines GPR transmission between the two countries. The finding that bilateral trade causes GPR to transmit across countries confirms the previous finding that trade or extensive economic interdependence increases the likelihood of interstate conflict (Barbieri 1996; Waltz 1979). The increased GPR transmission because of bilateral trade will reflect this increased likelihood of conflict between trading partners. Higher bilateral trade also implies more substantial economic interdependence between states. This interdependence may cause violence or unrest in one country to spill over to the countries' stronger trade ties. It may destabilize trade and economic relations, provoke distress migrations, and lead to complex humanitarian disasters in other countries. These are all various forms of geopolitical conflicts that lead to increased GPR. We have recently seen such GPR emerging from Syria and spreading to neighboring countries like Turkey, disrupting the geopolitical landscape in those countries. Hence, according to our results, bilateral trade does not seem to support trade's pacific benefit, which is contrary to Hegre et al. (2010). However, cultural and historical distance (colonial ties and language similarity) are irrelevant to this transmission. This may be because of sample limitations. Only a few countries in our sample have similar languages, and even fewer have colonial tries. It is not clear, therefore, whether these factors may explain GPR transmission. Although we still expect a relationship, a different dataset, such as Europe, may capture this relationship.

Our findings on geographical proximity confirm Blomberg and Rosendorff (2006), who provide evidence that distance and border significantly explain transnational terrorism flows. These findings also corroborate with those on the spread of a physical conflict (Buhaug and Gleditsch 2008; Hegre et al. 2010; Oneal and Russett 1999). As expected, contiguity increases while distance decreases the pairwise GPR transmission. Considering GPR transmission as information flow, our results also support the literature contending geographical proximity as an essential determinant of various information flows (Balli et al. 2015, 2017; Fidrmuc and Karaja 2013). Overall, it implies that geographical proximity facilitates information transmission of GPR. However, these findings contradict Virilio's (1986) view, who suggested that geographical territory has lost its significance and that speed of information has become more critical in geopolitics than the place.

Column (2) in Table 4 shows that country-specific (or domestic) attributes also play an essential role in the pairwise GPR transmission. At a 10% significance level, the budget deficit (or say fiscal imbalance) of $Country_i$ is an essential factor

in explaining DS_{ij}. Keeping other factors constant, a 1%[10] increase in the country's budget deficit increases DS_{ij} from $Country_i$ to $Country_j$ by 0.1020%. This indicates that a transmitter country's widening fiscal imbalance increases the GPR transmission from this country. However, the relationship between a receiving country's fiscal imbalance, i.e.,$Country_j$, and the GPR transmission is not found significant. Both countries' central government's debts also appear to be essential in the pairwise GPR transmission. A 1% (as percentage of GDP) rise in $Debt_i$ produces an increment of 0.017% in DS_{ij} at 5% significance level. Likewise, a 1% increase in $Debt_j$ increases DS_{ij} by 0.016% at 5% level. This suggests that both countries' rising debt levels increase the transmission of GPR shocks from them and the reception of the shocks coming toward them.

Our findings on fiscal imbalance and central government debt indicate bad neighborhood effects in interstate conflict literature; see Iqbal and Starr (2008), for instance. Consistent with their argument, our findings suggest that states undergoing economic problems would likely be contagious to their neighbors. Although these findings pertain to GPR information spillover, they might also be considered, supporting Balli et al. (2017) that countries' fiscal imbalances and financial liabilities are responsible for cross-country information spillovers of economic policy uncertainty.

Since the notion of geopolitics, and therefore GPR, is essentially linked to geography, the results on geographical size (area) shown in Colum (2) are of critical importance. We see that the geographical size of country i, denoted by $Log(Area_i)$, significantly determines the pairwise GPR transmission. The coefficient of $Log(Area_i)$ in column (2) means that a 1% rise in $Area_i$ produces an increment of 0.02% in DS_{ij} at 5% significance level. This suggests that the larger the geographical size of a $Country_i$, the higher the amount of GPR shocks transmitted from one country to another. Prominent examples of geographically large countries include Russia, Brazil, Saudi Arabia, and the USA. The dominant role of these geographically larger countries is also evident from both Fig. 1 and Table 3. In general, our finding on area corroborates with the consistent finding that countries' size influences the likelihood of interstate conflicts (Bearce and Fisher 2002; Hegre 2008; Kenneth 1962; Werner 1999; Xiang et al. 2007).

In summary, our results reveal a substantial amount of GPR transmission across the sample countries. Bilateral trade, border sharing, and distance are essential in transmitting GPR shocks from one country to another. While increases in debt burden, geographical size, and fiscal imbalance of a transmitting country tend to increase the pairwise GPR transmission, only a rising debt burden appears to exert a similar effect for the receiving country.

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[10] Note that budget deficit, debt (central government debt), and market capitalization of each country have been measured as a percentage of gross domestic product (GDP) of the respective country. See Appendix A for variable description.

3.3 Short- and long-term GPR transmission effects

Although the results presented so far may seem intuitive and broadly acceptable to the common audience, they may become contestable on the following ground. Throughout history, we have observed that some counties like Russia, Saudi Arabia, Israel, China, and the USA have experienced or caused the long-run effects of GPR. In contrast, for other countries in our sample, GPR may be a relatively short-term phenomenon. For example, the recent coup attempt in Turkey in 2016, or the military intervention in Thailand in 2014, has led to an increase in GPR countries in the short run. Consequently, the transmission or spillovers of GPRs for those countries may have only lasted for 1–3 months.

On the other hand, GPR resulted from events like 9/11 in the USA, the Russian Invasion in Afghanistan, and Israel and Palestine's conflict over the long run. It may be plausible to test the transmission of GPR in the short and long term. This would enable us to see whether GPR transmission and its drivers change when different time horizons are considered. In other words, this will provide us a way to test our results for the short- and long-term nature of GPR.

To do this, as mentioned before, Baruník and Křehlík (2018) offer a spillover model that allows us to estimate short- and long-term GPR transmissions. This model works with frequency bands that correspond to short-, medium-, and long-term transmissions. Considering the GPR phenomenon's nature and the GPR series' monthly frequency, we choose to work with only two frequency bands corresponding to short- and long-term GPR transmissions. The short-term spectral band refers to movements up to 3 months, and the long-term corresponds to movements from 3 to 100 months. The model's static version is applied using a forecast horizon of 100 months, and the lag lengths are chosen according to the Schwartz information criterion. The estimation results for short- and long-term GPR transmission are presented in Tables 4 and 5, while their pictorial diagrams are presented in Figs. 2 and 3, respectively.

In general, the key features of the short- and long-term GPR transmissions that emerged from Tables 4 and 5 are not much different from those given in Table 3. Interestingly, the total short-term GPR transmission (32%) in Table 4 is substantially larger than its long-term counterpart in Table 5 (7%). Also, note that the sum of these two transmissions would equal the total GPR transmission (39%) shown earlier in Table 3. A higher amount of short-term GPR transmission reflects that GPR fluctuations over 1–3 months have substantially displayed a stronger contagious character than the movements beyond 3 months. Similar to Table 3, Tables 4 and 5 also show that countries that transmit more GPR spillovers to other countries are also the ones that receive more. At the same time, the amounts of transmission are slightly higher than those of reception. Concentrating on Table 4, for instance, the USA (52%), Russia (46%), Brazil (45%), China (47%), and Mexico (40%) are among the highest contributors to the forecast error variance of the remaining countries. Likewise, the USA (43%), Russia (38%), Brazil (43%), China (45%), and Saudi Arabia (43%) are also the primary receivers of forecast error variance from the remaining countries. With a reduction in the amounts of transmission, a similar pattern is depicted in Table 5. Like Table 3, both the tables show that countries that

are bigger in terms of geographical size have greater participation in GPR spillovers. Again, with few exceptions, a higher spillover is observed among countries within the same geographical region.

Furthermore, the apparent patterns among countries regarding border sharing, distance, and trading behavior are also not very different from those observed in Table 3. Finally, the geographical clustering, shown in Figs. 2 and 3, also resembles the one depicted earlier in Fig. 1. Overall, from the patterns shown in Tables 4 and 5 and Figs. 2 and 3, one may be tempted to conclude that while the total amount of short-term GPR transmission is remarkably higher than that of its long-term counterpart, the other features of both transmissions remain seemingly unchanged. Nevertheless, we still need to ascertain whether this indeed is the case. Thus, we resort to the cross-sectional regression used to obtain the results presented in Table 6.

In order to examine whether the same factors continue to explain GPR in the short and long term, Table 7 again uses Eq. (12), but now with DS_{ij} calculated with the Baruník and Křehlík (2018) model. The results for short-term DS_{ij} are presented in columns (1) and (3), and long-term in columns (2) and (4). Comparing the short-term results to those in Table 6 for overall, the sign and significance are the same for the coefficients of $Log(Exports_{ij} + Imports_{ij})$, $Contigous_{ij}$, $Log(Distance_{ij})$, $Debt_i$, $Debt_j$, and $Log(Area_i)$.

Each of these coefficients becomes slightly weaker, with $BudgetDeficit_i$ losing its significance. For example, a comparison of column (1) of both the tables shows that the coefficient of $Log(Exports_{ij} + Imports_{ij})$ reduces marginally from 0.0027% (Table 6) to 0.0021% (Table 7). Likewise, the coefficient of $Contigous_{ij}$ shows a slight reduction, from 1.5410% in column (2) of Table 6 to 1.3880% in the same column of Table 7. The coefficients of most other (significant) determinants exhibit a similar tendency. The reduction in coefficient size is also evident from columns (3) and (4) of Table 7. To put things in perspective, remember that the total and pairwise GPR transmissions become weaker from Table 3 through Table 5, from overall to short-term to long-term GPR transmission. Once the coefficient reduction is coupled with this, it may be concluded that the role of bilateral and country-specific factors becomes weaker with lessening GPR transmission.

In columns (3) and (4) of Table 7, $Log(Exports_{ij} + Imports_{ij})$ continues to drive DS_{ij} in the long run. However, $Contigous_{ij}$ and $Log(Distance_{ij})$ lose their relevance. Also, while the coefficient of $BudgetDeficit_i$ becomes significant in this setting, a new factor, $Log(Area_j)$, becomes relevant. Other country-specific factors, namely $Debt_i$, $Debt_j$, and $Log(Area_i)$, also continue to be important in long-term GPR transmission, with coefficient signs being the same as those of Table 6. Overall, the main conclusion from these findings is that while the geographical proximity (border sharing and common distance) is an essential driver of overall and short-term (pairwise) GPR transmission, it plays no role in the pairwise long-term GPR transmission. As mentioned before, this finding supplements Blomberg and Rosendorff (2006). However, we contribute through the robustness check exercise that geographical proximity only drives overall and short-term GPR transmission, not the long-term one. In this same sense, this finding also contributes to the spread of a physical conflict debate (Buhaug and

Gleditsch 2008; Hegre et al. 2010; Oneal and Russett 1999). This is also supported by Virilio (1986), who suggested that territory has lost its significance and that speed has become more critical in geopolitics than the place.

To sum up, we employed the spillover model of Baruník and Křehlík (2018) to investigate further the short- and long-term nature of GPR transmission, which we obtained from Diebold and Yilmaz (2012). This exercise reveals that the basic features of GPR transmission, such as the geographical clustering and the pivotal role of individual countries, continue to hold for both short- and long-term GPR transmissions. However, this exercise unveils some additional features of this transmission, which are as follows: 1) The total and pairwise amounts of short-term GPR transmission are remarkably higher than that of its long-term counterpart but smaller than the overall GPR transmission computed earlier, meaning that the amount of GPR transmission becomes weaker from overall to short-term to long-term; 2) the role of bilateral and country-specific factors also becomes weaker with a reduction in the amount of GPR transmission; and 3) while geographical proximity (border sharing and common distance) is an essential determinant of overall and short-term GPR transmissions, it does not seem to their long-term counterpart. In this way, the investigation exercise confirms our primary findings on GPR transmission. It deepens our understating of this phenomenon by considering the short- and long-term aspects of GPR transmission.

4 Concluding remarks

This study quantifies GPR transmission across 19 countries. It explores whether bilateral and country-specific factors drive this transmission, using 19 news-based GPR indices of Caldara and Iacoviello (2018). Employing Diebold and Yilmaz's (2012) estimation methodology, a considerable amount of GPR transmission is found across our sample countries. A pictorial description of these results depicts a clear geographical clustering among GPRs and highlights the countries leading in each cluster. Using a gravity model framework, we find that certain bilateral and country-specific factors explain the pairwise GPR transmission. The results also hold for short- and long-term GPR transmissions computed using Baruník and Křehlík (2018). Investors, managers, and governments may find it helpful to incorporate these results in their decision-making processes.

In particular, institutional investors and multinational corporations are often concerned with making assessments and predictions about GPRs that arise from the local and international arena. For them, the bilateral linkages and country-specific indicators suggested in this study may help predict the course of GPR transmission between the two countries. These factors may also improve their assessments about a country's susceptibility to or resilience against foreign GPR shocks. Furthermore, since international investments usually spread across several geographical regions, the GPR's geographic clustering improves the understanding of the GPR concentrated regions and each country's GPR's role within those regions. In this way, this study provides a broader picture to help devise risk management strategies (perhaps

by buying political violence and/or terrorism insurance) and evaluating investment appraisals. Policymakers may also refer to this research when developing national security and counter-terrorism policies. Our findings suggest that governments stay attentive to the geopolitical events occurring in their neighborhood and the ones involving their trading partners. This is because GPRs caused by those events may have adverse consequences for the domestic geopolitical landscape. Since shirking bilateral trade and exploiting geographical factors is not possible, improving fiscal imbalances, lowering debt burdens, and strengthening the domestic economy are a few steps that may foster countries' resilience against foreign GPR shocks.

Although we estimated GPR transmission across countries, our estimation results are essentially cross-sectional, static, and based on news-based GPR indicators. Several questions remain and demand further investigation. Future research may investigate GPR transmission dynamics in terms of frequency, speed, volume, and time. In particular, researchers may dig deeper into the time-varying behavior of pairwise and total GPR transmission patterns. This may be achieved by applying the time-varying versions of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). Additionally, this research has strictly relied upon the gravity model framework and the factors specific to it for explaining the cross-country transmission of GPR. There is, however, an exhaustive list of factors and approaches that might explain other dimensions of this phenomenon.

In this study, we have not considered two aspects of the GPR transmission mechanism. That is, (1) we have identified a transmission medium, such as the internet, phone calls, television, and radio, that usually facilitate GPR transmission and (2) nor have we decomposed GPR into its sources, namely geopolitical events and geopolitical threats. The first aspect may be addressed by extending Weidmann's (2015) investigation, in which the authors explained conflict spread by international phone calls. The second aspect may be investigated by creating country-based GPR indices due to geopolitical events and threats separately. We understand that Caldara and Iacoviello (2018) have already developed two different GPR indices for the USA, namely GPR_Act and GPR_Threat. However, since the authors have not created the two indices for other countries, our study could not distill GPR transmission from this perspective.

An obvious limitation of the study is that it relies on GPR data of 18 emerging economies and the USA only. Since Caldara and Iacoviello (2018) have developed the GPR indices only for these 19 countries so far, our study is limited to these countries. This study's scope may well be broadened to a global scale once the GPR indices are available for a wide range of countries. Furthermore, it is essential to note that our sample includes only one African country, South Africa. We acknowledge this as a significant limitation of our study. Given the long history of internal conflicts in Africa, African countries would exhibit a higher GPR level than other countries, leading to an idiosyncratic GPR transmission pattern should more African countries be included in our sample. Despite these limitations, our paper moves the interstate conflict literature from the physical contagion of conflicts to the information contagion in the form of GPR transmission, setting a new direction to the field.

Table 6 Determinants of pairwise GPR transmissions (DS_{ij}) estimated using Diebold and Yilmaz (2012)

Variable	Gravity model	Gravity model (extended)
	(1)	(2)
	Total	Total
Intercept	5.430***	− 3.167
	(1.692)	(2.359)
$Log(Exports_{ij}+Imports_{ij})$	0.274***	0.384***
	(0.051)	(0.073)
$Contiguous_{ij}$	1.724***	1.540**
	(0.484)	(0.643)
$Colony_{ij}$	0.321	0.322
	(0.973)	(0.921)
$Common\ Language_{ij}$	0.535	0.508
	(0.343)	(0.433)
$Log(Distance_{ij})$	− 0.816***	− 0.500***
	(0.153)	(0.186)
$Budget\ Deficit_i$		0.102*
		(0.059)
$Budget\ Deficit_j$		0.071
		(0.059)
$Debt_i$		0.017**
		(0.008)
$Debt_j$		0.016**
		(0.008)
$Log(Area_i)$		0.196**
		(0.075)
$Log(Area_j)$		0.081
		(0.075)
$Log(Market\ Capitalization_i)$		− 0.086
		(0.213)
$Log(Market\ Capitalization_j)$		− 0.206
		(0.213)
R^2	30.30%	37.67%
Total observations	342	342

In table, the pairwise GPR spillover (DS_{ij}), as computed from the Diebold and Yilmaz (2012) model, is the dependent variable. The table reports the results of cross-sectional estimation with HAC standard errors in parentheses

*,**,***Indicate the significance of t-statistics at 10, 5, and 1% levels, respectively.

Table 7 Determinants of pairwise GPR transmissions (DS_{ij}) estimated using Baruník and Křehlík (2018)

Variable	Gravity model	Gravity model	Gravity model (extended)	Gravity model (extended)
	(1)	(2)	(3)	(4)
	Short term	Long term	Short term	Long term
Intercept	4.887***	0.543	− 1.554	− 1.613***
	(1.405)	(0.353)	(1.976)	(0.492)
$Log(Exports_{ij} + Imports_{ij})$	0.213***	0.061***	0.288***	0.096***
	(0.042)	(0.01)	(0.061)	(0.015)
$Contiguous_{ij}$	1.491***	0.233**	1.388**	0.152
	(0.402)	(0.101)	(0.536)	(0.133)
$Colony_{ij}$	0.09	0.23	0.101	0.22
	(0.809)	(0.203)	(0.771)	(0.192)
$Common\ Language_{ij}$	0.452	0.083	0.468	0.041
	(0.285)	(0.072)	(0.361)	(0.091)
$Log(Distance_{ij})$	− 0.700***	− 0.117***	− 0.458***	− 0.043
	(0.127)	(0.032)	(0.156)	(0.039)
$Budget\ Deficit_i$			0.081	0.021*
			(0.049)	(0.012)
$Budget\ Deficit_j$			0.065	0.005
			(0.049)	(0.012)
$Debt_i$			0.012*	0.006***
			(0.006)	(0.002)
$Debt_j$			0.013**	0.003*
			(0.007)	(0.002)
$Log(Area_i)$			0.151**	0.044***
			(0.063)	(0.016)
$Log(Area_j)$			0.054	0.026*
			(0.063)	(0.016)
$Log(Market\ Capitalization_i)$			− 0.066	− 0.02
			(0.178)	(0.044)
$Log(Market\ Capitalization_j)$			− 0.137	− 0.07
			(0.178)	(0.044)
R^2	30.11%	23.63%	36.16%	36.30%
Total observations	342	342	342	342

In table, the pairwise GPR spillover (DS_{ij}), as computed from the Baruník and Křehlík (2018) model, is the dependent variable. The table reports the results of cross-sectional estimation with HAC standard errors in parentheses

*,**,***Indicate the significance of t-statistics at 10, 5, and 1% levels, respectively.

Appendix A. Details of data and sources

Variable name	Definition	Source
$Exports_{ij}$	Share of the total exports of origin country i to country j relative to the total exports of country i. It is averaged for the period between 1985 and 2016	OECD STAN Bilateral Trade Database
$Imports_{ij}$	Share of the total imports of origin country i from country j relative to the total imports of country i. It is averaged for the period between 1985 and 2016	OECD STAN Bilateral Trade Database
$Contiguous_{ij}$	A binary variable that takes 1 if origin country i and country j are sharing a border, and 0 otherwise	CEPII
$Colony_{ij}$	A binary variable that takes 1 if origin country i has been a colony of country j, and 0 otherwise	CEPII
$Common\ Colony_{ij}$	A binary variable that takes 1 if origin country i and country j have remained under the influence of same colonial power, and 0 otherwise	CEPII
$Common\ Language_{ij}$	A binary variable that takes 1 if origin country i and country j share at least one common language, and 0 otherwise	CEPII
$Distance_{ij}$	Physical distance (in kilometers) between origin country i and country j	CEPII
$Budget\ Deficit_i$	Budget deficit (surplus) of country i as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
$Budget\ Deficit_j$	Budget deficit (surplus) of country j as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
$Debt_i$	Central government debt of country i as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
$Debt_j$	Central government debt of country j as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
$Area_i$	Geographical area (in squared kilometers) of country i. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)

Variable name	Definition	Source
Area_j	Geographical area (in squared kilometers) of country *j*. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
Market Capitalization_i	Stock market capitalization of country *i* as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
Market Capitalization_j	Stock market capitalization of country *j* as a percentage of its GDP. The figure is averaged for the period between 1985 and 2016	World Development Indicators (WDI)
DS_{ij}	Directional mean spillover (in %) of GPR transmitted by origin country *i* to country j	These amounts are calculated by authors by applying the spillover model of Diebold and Yilmaz (2012) on 19 GPR series of Caldara and Iacoviello (2018). These series are available on http://www.policyuncertainty.com/

Declarations

Conflict of interest The authors report no conflict of interest.

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