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Sources and Transmission of Country Risk

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We use textual analysis of earnings conference calls held by listed firms around the world to measure the amount of risk managers and investors at each firm associated with each country at each point in time. Flexibly aggregating this firm-country-quarter-level data allows us to systematically identify spikes in perceived country risk ("crises") and document their source and pattern of transmission to foreign firms. While this pattern usually follows a gravity structure, it often changes dramatically during crises. For example, while crises originating in developed countries propagate disproportionately to foreign financial firms, emerging market crises transmit less financially and more to traditionally exposed countries. We apply our measures to show that elevated perceptions of a country's riskiness, particularly those of foreign and financial firms, are associated with significant falls in local asset prices, capital outflows, and an increased likelihood of a sudden stop.

Key words: Country risk, Contagion, Textual analysis, Earnings calls

JEL codes: D21, F23, F30, G15

Researchers and policymakers often argue that global perceptions of risk are a major driver of international capital flows, financial contagion, and sudden stops. In addition, business leaders often cite crises in foreign markets where they may produce, sell, or be otherwise exposed as affecting their investment and employment decisions. Although such notions of country risk and its transmission across borders feature prominently in policy circles and boardrooms, documenting the sources of country risk and its channels of global transmission has proven more difficult.

This paper aims to provide a micro-to-macro approach to studying the sources and transmission of country risk. We measure perceived country risk at the firm-country-quarter level by computing the share of time that global firms' executives and investors spend discussing risks

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related to countries around the world. In particular, we apply natural language processing to more than 300,000 English-language conference call transcripts of publicly listed firms headquartered in 84 countries to measure the perceived risks and opportunities that each firm associates with each of the 45 largest economies in the world, collectively covering more than 90% of world GDP.

The primitive of our analysis and our key contribution is to measure how much risk firm i headquartered in country $d(i)$ associates with country c in quarter t. The major advantage of this granular approach to measuring country risk is that it allows for flexible aggregations: for example, we can separate global risks from those associated with particular countries, firms, and industries; separate the perceptions of different types of firms, such as financial versus non-financial firms; and trace the transmission of risk between countries. A second advantage is that our approach to measurement is based on the semantic content of the text. This enables us to distinguish variation in perceived risk (the second moment) from variation in perceived opportunities (the first moment) and to understand the sources of risks and opportunities that firms face.

After validating our granular measure, we successively aggregate it into three different dimensions. In the first step of our analysis we average across all firms in our sample to obtain an aggregate measure of risk for each of our forty-five countries: "Country Risk".[1] To validate these aggregate measures we show that increases in a country's perceived riskiness are accompanied by sharp declines in local equity prices, increases in equity volatility, and increases in sovereign credit default swap (CDS) spreads.

We then use these aggregate measures of country risk to systematically describe its sources. We first identify local and global spikes in risk ("crises") over the last two decades. Leveraging the semantic content of our measures, we use the excerpts of underlying text that drive the spike in the aggregate series to pinpoint the specific concerns that led investors and executives to focus their conversations on risks associated with the country in question. In this sense, our approach allows us to identify the perceived sources of variation in Country Risk without much guesswork.

Having identified and described the perceived sources of two global and thirty-six country-specific crises in our sample, we turn to studying the transmission of these risks across borders. To this end, we construct a measure of the aggregate flow of risk from each origin country to each destination country by calculating the average country risk firms headquartered in country d associated with country c at time t (that is, we average across all i in d). We refer to this measure as "Transmission Risk" and we find that during normal times, the transmission of risk across countries follows a gravity structure. In other words, firms on average worry more about risks originating in countries geographically closer to them, that speak the same language, and that were in a common colonial relationship.

However, despite this regular pattern of transmission of risk during normal times, we find that these patterns shift significantly during periods of crisis. To systematically quantify these shifts, we calculate the pattern of transmission for each of the country-specific crises identified in the first step of our analysis, and then regress this crisis-specific pattern onto the regular pattern of transmission from that origin country in non-crisis times. We argue that the predicted values, slope estimates, and R^2 from these regressions usefully characterize how a crisis associated with a particular origin country affects the perceived risk of firms based in other countries. For example, our analysis shows that the beginning of the Global Financial Crisis (GFC) in the U.S.

1. Thus we use "Country Risk" to mean the perceived risk associated with a given country, not as a synonym for sovereign default risk as it is occasionally used (*i.e.* Eaton *et al.*, 1986).

in 2008 and the start of the Coronavirus pandemic in China in the first quarter of 2020 are the two crises with the largest degree of global transmission in our sample: they transmit risk to firms in virtually all parts of the world. By contrast, crises originating in emerging markets (such as the Thai Floods of 2011 and the Egyptian Revolution of 2011) tend to come with strong bilateral transmission of risk: firms in countries traditionally exposed to the two countries increase their risk perceptions disproportionately, but there is a relatively limited impact on risks perceived by firms in other parts of the world.

Aside from variation in the degree of global and bilateral transmission, we also find that crises differ dramatically in the degree to which historical exposure can predict the transmission of risk during the crisis. For example, we find that the Fukushima nuclear disaster of 2011 engendered the crisis with the most irregular transmission pattern in our sample: We observe a strong transmission to countries that usually have relatively little perceived exposure to Japanese risk. One example of such irregular transmission is the effect of this event on German politics, where German engineering firms with no observable commercial links to Japan worry about the effect of the Japanese disaster on the prospects for nuclear power and the price of electricity in Germany.

We also use a similar regression-based approach to classify the extent to which crises are transmitted through financial or non-financial firms. We document a large degree of heterogeneity across crises; for example, financial firms experience nearly four times the increase in perceived risk as non-financial firms from the Italian sovereign debt crisis but only half the increase as non-financial firms from Russia's invasion of Crimea in 2014. Across the thirty-six crisis events in our sample, we find that sovereign debt crises and those originating in developed markets tend to have a significantly higher degree of financial transmission than other types of crises. Similarly, crises originating in emerging markets and sovereign debt crises tend to have relatively stronger bilateral transmission to historically exposed countries.

Having characterized the sources and transmission of perceived country risk during our sample, we then use our measures to study the role of a country's perceived riskiness for capital flows and sudden stops. Using our aggregate time series, we show that elevated levels of Country Risk coincide with foreign investors pulling capital out of the country: a one standard deviation increase in a country's perceived riskiness is associated with a 47% reduction in capital inflows relative to the sample mean. Importantly, this result holds even when global factors are controlled for. In this sense, our measures provide a useful contrast to a large literature that has demonstrated the importance of common (global shocks) for capital flows, but so far struggled to identify country-specific variables that can account for capital flows (Calvo *et al.*, 1996, *e.g.*).

To dig deeper into whose perceptions of risk matter most for allocations, we next create measures of aggregate Country Risk as perceived by different subsets of firms. That is, we obtain multiple aggregate measures of risk for the same country that allows us to distinguish the perceptions of foreign versus domestic firms and those of financial versus non-financial firms, among others. We find that it is the perceptions of foreign and financial firms that best account for the patterns of capital inflows, particularly those resulting from the purchase and sale of stocks and bonds (portfolio flows). We view this evidence as strongly supportive of the view that variations of the risk perceptions of financial firms and foreign firms are key to understanding the role of risk in the allocation of capital across countries and firms (Rey, 2015; Miranda-Agrippino and Rey, 2020; Jiang *et al.*, 2020).

Related Literature. This paper contributes to four major strands of the literature. First, a large literature studies the effects of time variation in global risk and risk premia on business cycles, asset prices, and capital flows. One branch of this literature studies how fluctuations in risks affecting global financial institutions generate common variations in asset prices and macroeconomic activity around the globe (Bekaert *et al.*, 2013; Rey, 2015; Miranda-Agrippino and Rey, 2020; Jiang *et al.*, 2020; Di Giovanni *et al.*, 2021; Akinci *et al.*, 2021). Another strand of this literature studies the role of time variation in country risk for determining the co-movement of asset prices, exchange rates, and capital flows across countries (Verdelhan, 2010; Colacito and Croce, 2011; Stathopoulos, 2017; Colacito *et al.*, 2018b). Other papers find that heterogeneity in the stochastic properties of countries' loadings on global risk is key to several puzzles in international economics (Lustig *et al.*, 2011; Hassan, 2013; Gourio *et al.*, 2013; Colacito *et al.*, 2018a; Richmond, 2019). The predominant approach in this literature is to infer variation in risk from asset prices and other aggregate variables. We contribute by providing a measurement framework that can directly quantify risks perceived by decision makers at global firms, systematically distinguish perceived global from country-specific risks, and separate variation in risk (the second moment) from variation in positive and negative shocks (the first moment). Beyond providing data to test these theories, our findings that the risk perceptions of global firms co-vary with asset prices and capital flows, and that financial firms' perceptions appear particularly impactful in this regard, provide direct empirical support for two key predictions in this literature.

Second, we contribute to a growing literature that generates measures of risk from the text. Baker *et al.* (2016) use newspapers to measure economic policy uncertainty. Hassan *et al.* (2019) and Handley and Frank Li (2020) use the transcripts of earnings conference calls and 10K disclosures to measure firm-level risks in the U.S., and Ahir *et al.* (2018) use the Economist Intelligence Unit (EIU) country reports to construct country-level indices of economic uncertainty by counting the frequency of synonyms for risk or uncertainty within these reports. We differ from these existing approaches in two main respects. First, measuring risk at the firm-country-quarter-level allows us to flexibly decompose perceptions of sub-groups of decision makers and to measure the transmission of risk from countries to firms. Second, these same decompositions enable us to understand directly from the underlying text what events drive a given peak in risk. In this sense, our work relates closely to Calomiris and Mamaysky (2019), Baker *et al.* (2021) and Indarte and Xu (2021) who explore the origins of fluctuations in asset prices using textual analysis of newspaper articles.

Third, a large literature studies contagion, the notion that crises can spread suddenly and in unpredictable ways across borders—a perennial concern for policymakers (Forbes, 2012). A major challenge in this literature is that it is generally hard to measure how shocks, particularly shocks to perceived risks, propagate across borders. Existing approaches tend to rely on inferring the degree of contagion from asset prices (Forbes and Rigobon, 2002; Bekaert *et al.*, 2014b; Bae *et al.*, 2015), or measure the propagation of specific shocks between customers and suppliers (Boehm *et al.*, 2019; Carvalho *et al.*, 2021). Hassan *et al.* (2020) use textual analysis to study the international spillovers of Brexit-related risks during one specific episode. We contribute by providing systematic measurement of spillovers of perceived risks across borders, and by showing that the pattern of transmission of risks can indeed differ significantly between crisis and non-crisis periods.

Finally, our work contributes to the literature on global capital flows and sudden stops. Calvo *et al.* (1996) demonstrated the importance of shocks emanating from global financial centres for fluctuations in capital flows, emphasizing the importance of "push factors". Fratzscher (2012) examines the importance of these push and pull factors during the period of the global financial crisis. Forbes and Warnock (2012) and Broner *et al.* (2013) examine the determinants of movements in gross capital flows. We use our new measures to demonstrate the importance of perceptions of country-specific risk, particularly those of global financial firms, in driving global capital flows. In this sense, we bridge the gap between push-and-pull factors by showing the importance of a country-specific risk factor that comes from the measurement of the beliefs of a common set of global firms and investors.[2]

The structure of the paper is as follows. Section 1 introduces our methodology for measuring country risk at the firm level and defines and validates our measures at the micro and macro levels. Section 2 studies the time series of Country Risk and identifies crises and their sources. Section 3 examines the transmission of risk across countries in crisis and non-crisis times. Section 4 applies our measures to study capital flows. Section 5 concludes.

1. MEASURING COUNTRY RISK AT THE MICRO LEVEL

In this section, we describe how we use natural language processing to measure $CountryRisk_{i,c,t}$ at the firm-country-quarter level and then aggregate it to various levels for our analysis. We begin with a description of the micro-level methodology and data and then turn to the aggregation framework. Our objective is to measure the amount of time executives and investors at firm i spend discussing risks associated with country c in their earnings conference call held in quarter t, $CountryRisk_{i,c,t}$. To automate this process, we will use standard tools from natural language processing in combination with training libraries sourced from the Economist Intelligence Unit Country Commerce reports to determine which phrases and parts of text refer to which countries.

1.1. *Conference call transcripts*

The core of our dataset is the complete set of 306,589 English-language earnings conference call transcripts from Refinitiv Eikon, 2002–2020. These conference calls cover 12,326 firms that are headquartered in 84 countries. Generally, firms have four calls per year, timed to coincide with earnings releases. A standard conference call takes the form of a management presentation followed by a question and answer session with the firm's analysts. On average, each call lasts around 45 minutes (Matsumoto *et al.*, 2011). In order to prepare the earnings call transcripts for analysis, we remove all metadata and non-alphabetic characters but do not force words to be lowercase in order to facilitate the subsequent country name matching (*e.g.* to distinguish Turkey from the animal turkey).

Table 1 summarizes our country coverage for the largest forty-five economies in the world. Of the 11,829 firms, 6,623 are headquartered in the U.S. The next three countries with the highest coverage are Canada, the U.K., and Australia with 918, 548, and 434 firms, respectively. This ordering reflects Eikon's focus on English-language transcripts and firms headquartered in English-speaking countries are, of course, more likely to conduct their conference calls in English.[3] Outside of the four major English-speaking economies, the number of firms covered by country aligns closely with each country's share of world GDP (see Appendix Figure 1). For thirty-five out of the forty-five largest economies, we have data from at least twenty locally headquartered firms, and many firms report substantial (Worldscope segment) sales to almost all of our countries except for Iran and Pakistan. The smallest economy in our sample (Hungary) accounts for 0.18% of the world's GDP in 2019. We thus expect a number of our sample firms having at least some concern about the goings on in each of the forty-five countries.

2. Bekaert *et al.* (2014a) examine the role of political risk, estimated from sovereign spreads in driving foreign direct investment. Kalemli-Özcan (2019) explores the differential transmission of risk movements for emerging and advanced economies.

3. Our analysis uses the headquarters country of a firm, rather than the legal incorporation to more closely map to economic decision-making. See Coppola *et al.* (2021) for a detailed discussion of these issues.

TABLE 1
Sample selection of firms with earnings calls

	# of firms (all years)	# of sales link (any year)	% of world GDP (2019)	# of firms (2019)	% of 2019 market capitalization
Argentina	20	94	0.68%	16	44.9%
Australia	434	385	1.78%	313	63.6%
Belgium	45	120	0.59%	28	71.5%
Brazil	178	272	2.17%	135	65.8%
Canada	918	886	2.03%	477	90.5%
Chile	31	88	0.31%	24	58.1%
China	349	738	17.08%	165	21.3%
Colombia	16	67	0.38%	15	85.4%
Czech Republic	6	57	0.26%	6	70.5%
Egypt	8	28	0.48%	4	21.8%
France	161	405	3.13%	122	83.4%
Germany	219	698	4.30%	152	84.5%
Greece	41	27	0.24%	19	59.0%
Hong Kong	115	113	0.40%	68	49.7%
Hungary	4	40	0.18%	4	87.9%
India	362	193	3.21%	263	64.6%
Indonesia	18	66	1.25%	9	12.6%
Iran	0	1	0.53%	0	n/a
Ireland	73	90	0.44%	53	79.9%
Israel	114	74	0.42%	58	47.3%
Italy	109	247	2.29%	70	86.9%
Japan	230	595	5.46%	146	39.3%
Malaysia	23	112	0.44%	14	25.6%
Mexico	98	308	1.50%	65	67.9%
Netherlands	104	207	1.00%	67	80.1%
New Zealand	62	85	0.24%	47	74.5%
Nigeria	14	29	0.60%	10	41.7%
Norway	96	102	0.49%	71	83.9%
Pakistan	4	8	0.39%	0	n/a
Philippines	20	61	0.47%	12	19.7%
Poland	32	86	0.68%	26	61.7%
Russia	54	101	1.75%	35	73.1%
Saudi Arabia	3	31	0.81%	2	5.3%
Singapore	56	208	0.42%	35	49.0%
South Africa	96	96	0.43%	76	83.4%
South Korea	45	233	1.96%	31	30.9%
Spain	75	199	1.58%	59	87.2%
Sweden	198	118	0.66%	154	80.2%
Switzerland	125	145	0.91%	97	88.4%
Taiwan	49	179	n/a	26	37.7%
Thailand	24	74	0.55%	19	29.9%
Turkey	27	61	1.19%	24	39.8%

(continued)

TABLE 1
Continued

	# of firms (all years)	# of sales link (any year)	% of world GDP (2019)	# of firms (2019)	% of 2019 market capitalization
U.K.	548	990	3.81%	374	85.0%
U.S.	6,623	1,319	23.81%	3,219	94.6%
Venezuela	2	36	n/a	0	n/a
Total	11,829	10,072	91.3%	6,610	57.5% (mean)

Notes: This table shows for the forty-five countries for which we have text-based measures of country exposure, risk, and sentiment, the number of firms in our data (Column 2), the number of firms that report part of their sales to the country (Column 3), the share in 2019 world GDP (Column 4), the number of firms in our data in 2019 (Column 5), and the percentage of all Compustat's firms' market capitalization by firms in our sample (Column 6). The last row shows the sum for Columns 2–5, and the mean for Column 6. Firms in our sample are all firms for which we have earnings calls between 2002 and 2019; the sales link is taken from Worldscope and defined as the number of firms that report part of their sales to the country at any point between 2002 and 2017; GDP is the real GDP (constant 2015, USD) from the World Bank (indicator `NY.GDP.MKTP.KD`); and market capitalization is defined as share price `prccd` (converted to USD where needed) multiplied by outstanding shares `cshoc` (if there are multiple stock issuances `iid` for a firm, we use the primary issuance).

Figure 1 shows how this coverage evolves over time. In 2003, our transcripts cover 85% of the U.S. and 27.7% of the (non-U.S.) market capitalization of the forty-four other large economies. Over time, the coverage both inside and outside of the U.S. increases markedly so that by the end of the sample, our data cover 93.7% of U.S. and 59.2% of non-U.S. market capitalization. By 2019, our transcripts account for more than 50% of local market capitalization in twenty-six of our forty-five countries. Of the remaining nineteen countries, more than half (eleven) cover more than 25% of the local market cap. The countries with lower coverage are Egypt (21.8%), China (21.3%), the Philippines (19.7%), Indonesia (12.6%), and Saudi Arabia (5.3%).[4] We have no transcripts from Iran, Pakistan, and Venezuela in 2019—which of course does not prevent us from measuring foreign firm's perceptions of the risks associated with these countries.

Consistent with this pattern of relatively high firm coverage when weighting by market capitalization, Appendix Figure 2 shows that the largest listed firms in any given country are disproportionately likely to appear in our dataset. In this sense, one can best think of our measures as capturing the concerns of multinational firms and global investors. Consequently, we do not expect our measures to be sensitive to risks that are not commercially relevant for these global firms. For example, large and devastating floods in Mozambique may be enormously consequential for humanity, but we do not expect them to feature in earnings calls if they are not commercially relevant for global firms. Even so, and particularly for the U.S. and Canada, the data also include smaller listed firms. All of our main results are robust to stratifying the sample of calls in a variety of ways, for example by systematically excluding smaller firms.

1.2. *Country-specific training libraries*

A key step in measuring country risk is to identify when the conversations in conference calls focus on particular countries. To do so, we assemble a training library $\mathbb{T}^c$ for each of our $c = 1, \ldots, C$ countries. The primary source for our training library is the set of Country Commerce Reports published by the Economist Intelligence Unit. The Economist describes these reports as "a practical guide to a country's business regulations and business practices."[5] The reports offer

4. After the listing of Saudi Aramco, which held its first earnings call in May of 2020, this coverage is up to approximately 80% of market capitalization, reflecting Aramco's outsized role in the Saudi economy.

5. See the description in https://store.eiu.com/product/country-commerce.

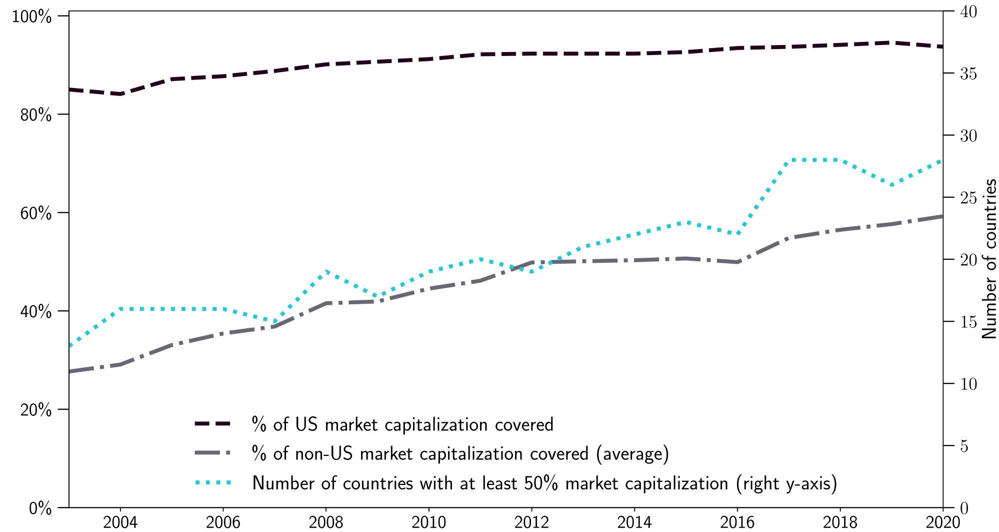


FIGURE 1

Coverage of firms over time

Notes: This figure plots the per cent of market capitalization for firms based in the U.S. and in countries around the world that the earnings call data cover (left *y*-axis), and the number of countries for which the earnings call data covers at least 50% of market capitalization (right *y*-axis). The list of non-U.S. countries is the same list of forty-five countries as the countries for which have created $CountryRisk_{c,t}$. A firm's market capitalization is calculated based on Compustat North America and Global as follows: `prccd` × `cshoc` at the last available data point of each calendar year, where `prccd` is the close market prices and `cshoc` is the number of common shares outstanding. Prior to multiplying, we convert non-U.S. dollar market prices into U.S. dollars. If a firm has multiple issuances (`iid`), we use the market capitalization of the primary issuance. Brazil and Venezuela are excluded from the calculation of the per cent of non-U.S. market capitalization covered due to irregularities in their data early in the sample period

a number of desirable features for our purposes. First, because the reports are designed to cover the country's key economic institutions, they include a range of terminology relevant to each country. Second, the reports take a standardized form, allowing us to reliably compare across countries. Third, because the reports are released regularly, they allow us to add new terms to our training library as they enter into the discourse. Of the fifty-six countries for which Country Commerce Reports exist, we focus our analysis on the largest forty-five economies, collectively covering 91.3% of world GDP in 2019.[6]

For each of these countries, we obtain all reports for 2002–2019, remove non-alphabetic characters, and remove all pairs of adjacent words (bigrams) that are likely to be used in conversational language.[7] We collect the remaining text in a single training library for each country. In addition, we obtain a separate list of the country's adjectival and demonymic names, the names of administrative subdivisions, and the names of towns with more than 15,000 inhabitants in 2018, to which we give special attention below.[8]

6. We thus exclude Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Kenya, Nicaragua, Panama, Peru, Uruguay, and Vietnam, as we believe discussions of these economies are too infrequent to return reliable measures. Nevertheless, all of our main findings are robust to including these countries in the analysis.

7. To this end, we use all bigrams from the University of Santa Barbara Corpus of Spoken American English Bois *et al.* (2000–2005), which is a large collection of transcripts of "naturally occurring spoken interaction from all over the United States." We pre-process the speech corpus in the same way as we pre-process the Country Commerce Reports; in addition, we remove bigrams that contain a country or city name.

8. All adjectival and demonymic forms of the country name are from Wikipedia and the CIA World Factbook; the remaining names of places and towns are from geonames.org.

We then assign to each bigram a weight that indicates how strongly it is associated with discussions of the country. To this end, we employ a simple pattern-based sequence classification method, which identifies the bigram's relevance for a given country as the interaction of two terms (Sparck, 1972; Salton and McGill, 1983; Salton and Buckley, 1988).[9] The first is the bigram's relative frequency in the training library of country c; the second is the log of the bigram's inverse frequency across training libraries—a penalty for bigrams that also appear in the training libraries of many other countries:

$$\omega(b,c) = \frac{f_{b,T^c}}{B_{T^c}} \times \log(N_C/N_b), \tag{1}$$

where f_{b,T^c} denotes the frequency of bigram b in the training library of country c, B_{T^c} is the total number of bigrams in the same training library, N_C is the total number of training libraries, and N_b is the number of training libraries in which b occurs at least once. The first term, commonly denoted "term frequency" (tf), thus gives more weight to bigrams frequently used in c's training library. The second term, commonly denoted "inverse document frequency" (idf), gives more weight to bigrams that do not also occur in discussions of most other countries. For example, while the bigram "in Brussels" may be frequent in the training library for Belgium, it also appears in the training libraries of many other EU countries, so that the bigram is likely less informative about whether or not a given text excerpt contains discussions of Belgium.

To make allowance for the fact that countries and places are often described by single words (unigrams) and our training libraries may not contain all relevant combinations of these unigrams with other words, we separately construct a weight for all unigrams contained in the list of country and place names mentioned above using the same formula (1). We then use this (unigram-based) weight as a minimum weight for all bigrams that contain the unigram in question. Finally, because the name of the country itself is particularly important for our exercise, we assign to it the maximum $\omega(b,c)$ of any bigram or unigram containing the country's name.[10] For this step, we convert all two-word country names (such as "United States") to unigrams so that all country names are treated equivalently.

Table 2 gives intuition for the workings of our algorithm by showing the top twenty bigrams by $\omega(b,c)$ in our training library for Turkey, Japan, and Greece. While for each country variants of the country's name are among the most important bigrams ("Turkish", "Japanese", "Greek"), we can see how successful the Country Commerce Reports are in identifying important country-specific phrases and institutions. For instance, in Panel A for Turkey, we see that the second most important bigram is "Gazette No" and the fifth is "Official Gazette", capturing the Gazette, which is the official publication form in Turkey for new legislation and other official announcements. In the case of Japan, the capitalized bigram "Economy Trade", as well as the bigrams "Industry METI" and "the METI" all reference to the powerful Ministry of Economy Trade and Industry. Similarly "the JFTC" and "the JPO" refer to the Japanese Fair Trade Commission

9. We could in principle substitute this approach with more advanced machine learning techniques which also allow researchers to infer how relevant a given phrase b is in discussions of country c. For example, Gentzkow *et al.* (2019) or Davis *et al.* (2020) use text inverse regression (developed by Taddy (2013, 2015) and further extended by Kelly *et al.* (2019)) to identify relevant phrases in a different context. We believe that in our context the more traditional approach is preferable because of its simplicity and the ease with which it allows us to directly analyse the underlying text.

10. Because country names themselves tend to appear as parts of lists in the Country Commerce Reports (*e.g.* as part of a list of bilateral withholding tax rates), they sometimes get substantially down-weighted. This is because their *idf* becomes small as they appear across more Country Commerce Reports. Assigning a floor as described here remedies this problem.

TABLE 2
Top 20 ngrams in the training library of Turkey, Japan, and Greece

Ngram	$\omega(b,c)$	Frequency	Ngram	$\omega(b,c)$	Frequency
PANEL A: TURKEY					
Turkey/Turkish	805.22	2,738	the Undersecretariat	87.61	112
Gazette No	246.57	398	Izmir	82.21	87
Turk Eximbank	171.04	181	the Directive	76.56	135
Ankara	144.58	153	in prioritydevelopment	76.54	81
Official Gazette	131.89	495	prioritydevelopment regions	74.65	79
of Turkeys	128.48	187	in Turkeys	73.71	78
Istanbul	127.94	244	Region VI	71.18	91
the lira	114.34	121	Undersecretariat of	71.18	91
the GDFI	94.50	100	Patent Institute	70.01	113
an AS	88.63	129	the AKP	68.04	72
PANEL B: JAPAN					
Japan	244.15	7,076	Standards Law	83.63	206
Economy Trade	215.39	466	Japanese	81.28	3,801
the JFTC	207.15	371	Tokyo	81.13	626
Health Labour	138.47	248	Antimonopoly Law	78.70	215
Industry METI	136.24	244	Labour Standards	75.78	207
the METI	115.58	207	AntiMonopoly Law	73.89	182
The JFTC	107.21	192	inhabitant tax	73.49	159
the JPO	86.55	155	Okinawa	72.03	129
the Diet	85.99	154	and Welfare	70.96	246
enterprise tax	84.58	183	Osaka	69.42	171
PANEL C: GREECE					
Greece/Greek	607.83	2,897	The ND	73.09	114
Athens	339.67	640	New Democracy	69.89	109
Hellenic	249.73	649	Greeks	64.75	101
ND government	130.15	203	Strategic Reference	61.55	96
Piraeus	127.91	241	gov gr	61.55	96
Share sale	88.48	138	Attica	59.63	93
an AE	80.78	126	ministerial decisions	59.20	127
Thessaloniki	80.67	152	Alpha Bank	58.34	91
by Law	79.83	511	objective value	57.70	90
the EA	76.30	119	of Development	54.90	236

Notes: This table lists the top twenty ngrams when sorted on $\omega(b,c)$ (the $tf \times idf$ in the training library) for three selected countries. Column 2 shows the $\omega(b,c)$ of the ngram, which is the frequency of the ngram in its country-specific library divided by the total number of ngrams in that library (tf) multiplied by the log of the number of country libraries divided by the number of country libraries that contain the ngram (idf); and Column 3 shows the frequency of the ngram in the country-specific library. A country-specific training library consists of (a) all adjacent two-word combinations (bigrams) from the country's Economist Intelligence Unit (EIU) Country Commerce Reports published between 2002 and 2019; and (b) all unigrams in the EIU that are also in a custom country-specific names list that consists of country names, region names, and city names of cities with more than 15,000 inhabitants in 2018 (from Geonames.org), and all adjectival demonymic forms of the country name (from Wikipedia and the CIA World Factbook). We impose that an ngram that is a country name gets assigned the highest $tf \times idf$ of all ngrams in the country library that contain the country name.

and the Japanese Patent Office, respectively. For Greece, we see that the fifth most important bigram is "ND government", a short-hand referring to the "New Democracy" centre-right political party; and "an AE" is similar to a U.S. limited liability company. In all of these cases, these phrases would be obvious to experts in the area, but there would be no ex ante way to say which names and phrases would be most useful in identifying conversations about a given country. Our approach—systematically extracting the expertise embedded in the Country Commerce Reports to identify the country in question—is therefore more comprehensive than simply waiting for a call participant to say "Turkey" or "Japan".

1.3. *Measuring firm-level country risk, sentiment, and exposure*

With our country-specific training libraries in hand, we can turn to the measurement of country risk at the firm level. To create our measure of country risk, we build on the methodology of Hassan *et al.* (2019) by counting the number of mentions of bigrams indicative of conversations about country c in conjunction with a synonym for risk or uncertainty:[11]

$$CountryRisk_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \{1[|b-r| \leq 10] \times \omega(b,c)\}, \tag{2}$$

where $b = 0, 1, \ldots B_{it}$ are the bigrams contained in the earnings call of firm i at time t and r is the position of the nearest synonym of risk or uncertainty.[12] Country Risk thus counts the number of mentions of country c within ten words of a synonym for risk or uncertainty, weighted by $\omega(b,c)$. This means bigrams that the training library more confidently ascribes to a given country also receive more weight. We then divide this sum by the total number of bigrams in the transcript to account for differences in the length of the earnings call.

To complement our key measure of country risk, we also create measures of firm-level exposure and sentiment. Country Exposure proxies for the overall perceived exposure a firm has to a given foreign country—it is a weighted count of the number of mentions of a given foreign country, again divided by the length of the transcript:

$$CountryExposure_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \omega(b,c). \tag{3}$$

Finally, we construct a measure of country sentiment, which we primarily use as a control for whether the firm receives good or bad news about its activities relating to country c. Instead of conditioning on bigrams appearing close to a synonym for risk, this measure counts positive or negative tone words ("sentiment") used in conjunction with the same country-specific bigrams:

$$CountrySentiment_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left\{ \left(\sum_{g=b-10}^{b+10} S(g) \right) \times \omega(b,c) \right\}, \tag{4}$$

where the function S assigns $+1$ to positive tone words and -1 to negative tone words included in the library of tone words provided by Loughran and McDonald (2011). Appendix Table 2 lists the top 100 positive and negative sentiment words by frequency.

1.4. *Aggregations of country risk*

Having measured $CountryRisk_{i,c,t}$ as the share of the conversation between management and investors at firm i headquartered in country $d(i)$ spent discussing risks associated with country c—note that this notion of risk captures all types of risk that listed firms may be concerned about, including (but not limited to) regulatory, supply chain, sovereign debt, environmental and

11. We obtain all synonyms for risk, risky, uncertain, and uncertainty from Oxford Dictionary. Appendix Table 1 lists the top 100 risk synonyms.

12. While one might worry this measure would be contaminated by negated phrases such as "less risky", from examining the underlying text snippets we concluded this is not a significant concern in practice.

political risks—we now turn to using this micro, firm-based, measure of country risk to achieve three core objectives.

First, to construct country-level measures of risk, we aggregate $CountryRisk_{i,c,t}$ across a set of firms K,

$$CountryRisk^{K}_{c,t} = \frac{1}{N_K}\sum_{i\in K} CountryRisk_{i,c,t}, \tag{5}$$

where N_K is the number of firms of type K in the dataset. In other words, $CountryRisk^{K}_{c,t}$ captures the average perceived risk emanating from country c at time t for the set of firms K. The power of this approach is that performing this type of aggregation for different sets of firms K will deliver measures of country risk capturing the risk perceptions of different types of firms around the world. While our primary measure includes the full set of firms ($K = ALL$) for which we can measure $CountryRisk_{i,c,t}$, we also consider separately the perceptions of foreign firms (*NHQ*), financial firms (*FIN*), American firms (*U.S.*), and firms only in a particular industry.

Second, we measure the aggregate transmission of risk from each origin country to each destination country at each point in time by summing over the risk that all firms based in country d perceive in country o at time t:

$$TransmissionRisk_{o\rightarrow d,t} = \frac{1}{N_d}\sum_{i\in d} CountryRisk_{i,o,t} \tag{6}$$

The measure is designed to capture how much risk is transmitted from country o to country d. We refer to this measure as Transmission Risk.

Because the latter aggregation sometimes relies on only a few dozen observations, we usually replace

$$CountryRisk_{i,c,t} \approx CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}, \tag{7}$$

in (6), where $\widetilde{CountryRisk}^{NHQ}_{c,t}$ is our aggregate measure of country risk as perceived by all foreign firms from (5), after projecting it on country and time fixed effects and adding in the full sample mean (which is sufficient to ensure that the term remains positive throughout). We find this procedure reduces measurement error because it relies on individual transcripts only to capture firm-quarter level variation in exposure, but harnesses information from the full sample to measure over-time variation in the origin country's riskiness. This reduction in measurement error makes the origin-destination-quarter level observations from (6) easier to interpret (in that it reduces spurious variation), but has little effect on our econometric results.

Finally, we aggregate our measures across all firms and destinations to create a text-based measure of global risk as the average of $CountryRisk_{i,c,t}$ over firms and countries

$$GlobalRisk_t = \frac{1}{N_I}\frac{1}{N_C}\sum_{i\in I}\sum_{c\in C} CountryRisk_{i,c,t}.$$

While our focus is on country risk, we conduct analogous aggregations of the exposure and sentiment firm i has towards country c at time t, and use them as controls where appropriate.

1.5. *Validation and summary statistics*

Before turning to our analysis of country risk, we validate our measures at the micro and macro levels.

TABLE 3
Country exposure and observed firm links

	$CountryExposure_{i,c}$ (std.)				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(Headquarter)_{i,c}$	2.337***			2.229***	2.943***
	(0.040)			(0.078)	(0.102)
$\mathbb{1}(Exports)_{i,c}$		1.225***		1.026***	1.195***
		(0.025)		(0.025)	(0.029)
$\mathbb{1}(Subsidiary)_{i,c}$			0.595***	0.262***	0.299***
			(0.008)	(0.006)	(0.007)
R^2	0.114	0.059	0.059	0.168	0.205
N	533,925	215,325	387,225	168,570	168,570
Country FE	no	no	no	no	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the firm-country level. All variables are as defined in Section 1; summary statistics are provided in Panel A of Table 4. Column 5 includes country-fixed effects. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Firm-level Exposure In Table 3, we validate our firm-level exposure measure. In particular, we regress firm i's average exposure to country c, $CountryExposure_{i,c} \equiv (1/T)\sum_t CountryExposure_{i,c,t}$ on other firm-level variables that should correlate with a firm's material exposure to a country. If our text-based exposure measure is systematically behaving as it should, we would expect it to co-vary strongly with these variables.

The first variable we consider is whether the firm in question is headquartered in country c as listed in Compustat (the most recent `loc` variable, which indicates the country of the headquarter of a firm). Second, we classify whether firm i reports sales to country c at any time. If a country is an important export market for a firm, we would expect to call participants to discuss that particular country more during their earnings calls. To measure this variable, we use the Geographic Segment data from Worldscope.[13] Third, we use a firm's subsidiaries in 2016, as listed in Bureau van Dijk's Orbis database, as another observable exposure to a country. If firm i has a subsidiary in country c, we would expect it to discuss that country more during its earnings calls.

The regressions in Table 3 provide strong confirmation for our measure. Firms are 2.3 standard deviations more exposed to their headquarter country than other firms, and firms with an export link are on average 1.2 standard deviations more exposed than other firms. In the third column, we repeat the exercise using a dummy variable for whether a firm has a subsidiary in a given country. We once again find that the presence of a subsidiary dramatically increases firm-level exposure to a country. These findings continue to hold in Columns 4 and 5, when we consider the three variables simultaneously with and without country-fixed effects, respectively.

13. This data is extracted from annual reports, where under GAAP and IFSR accounting rules, firms need to report all sales destinations from which they earn more than 10% of their revenue or have a "material interest." We, therefore, classify the firm as exporting to a particular country if the country is listed in this report in 2016. However, note this coarse measure will miss some export markets, as a firm may choose, for instance, to report having 20% of its sales to "Asia" rather than reporting 9% to Japan, 9% to China, and 2% to Thailand. In this instance, the Worldscope data would not classify the firm as having sales links to China or Japan.

Aggregate Country Risk and Sentiment Having documented the reliability of our exposure measure at the firm level, we next turn to the aggregate measures. Table 4 presents summary statistics for our measures of country risk and sentiment.[14]

First, consistent with recent work that has emphasized the co-movement of global risk across countries (Rey, 2015; Miranda-Agrippino and Rey, 2020), we find a strong common component in both Country Risk and Country Sentiment. In particular, the first principal component of Country Risk explains 62.1% of country-level variation. Similarly, we find that that the first principal component of Country Sentiment explains 87.5% of the country-level variation. We return to this issue in Section 4, where we show direct evidence that these global co-movements give rise to episodes of retrenchment in capital flows.

Second, we find that the mean within-country correlation between $CountryRisk_{c,t}$ and $CountrySentiment_{c,t}$ is −0.31. As argued by Berger *et al.* (2020), we can thus confirm that the first moment (Country Sentiment) and second moment (Country Risk) are negatively correlated, where higher risk is often associated with lower sentiment (that is, bad news).[15] Consistent with this pattern, we also find that Country Risk is strongly countercyclical, with cyclicality measured using country-level real GDP growth rates. By contrast, Country Sentiment is pro-cyclical.[16]

Nevertheless, the two series are not mirror images of each other, and they often diverge for economically important reasons. For instance, in Appendix Figure 3, we plot the time series of Country Risk and Country Sentiment (reversed) for Mexico. While the correlation between the two variables is −0.32, we note a major divergence between the two around the fourth quarter of 2016. At the time, the election of Donald Trump and his harsh rhetoric against Mexico caused a major spike in perceived risk in Mexico, yet Sentiment barely moved. We view this as validating our use of Sentiment as the first moment and Risk as the second moment: Trump's election did not change the mean economic outlook for Mexico, but it did dramatically increase its perceived volatility going forward. This example holds true more generally, where both measures have meaningful independent variation, as we show below.

Finally, we provide further validation for these measures by documenting their strong co-movement with asset prices. Table 5 shows that when Country Risk increases and Country Sentiment decreases stock returns fall. In particular, in Column 2, a 1% increase in Country Risk is associated with a 0.213 (s.e. = 0.035) percentage point drop in the country's (MSCI) stock return index, while a 1% increase in Country Sentiment is associated with a 0.267 (s.e. = 0.050) percentage point increase in stock returns. The following columns show a similar pattern for CDS spreads: as country risk rises and sentiment falls, CDS spreads significantly increase. By contrast, Column 6 shows that changes in realized volatility are *not* significantly associated with changes in Country Sentiment (the first moment), but instead load only on variation in Country Risk (the second moment), bolstering our confidence that our measures of sentiment and risk

14. To facilitate the interpretation of regression coefficients, we divide each measure by its standard deviation in the panel. In addition, the table presents summary statistics for the key financial and macroeconomic variables that we will use for the validation of our measures and the empirical analysis.

15. Thirty synonyms for risk or uncertainty used in our sample of earnings conference calls also have a negative connotation according to this definition. Examples include "exposed", "threat", "doubt", and "fear". Taking into account their frequency as found in our sample of earnings calls, this represents 9.4 and 0.97% of all synonyms for risk and negative sentiment, respectively. Our measures thus explicitly allow speakers to simultaneously convey risk and negative sentiment. However, this does not interfere with our ability to disentangle risk from sentiment: By definition, when we include both measures for risk and sentiment in a regression, we control for any variation that is common to each other (as a result of overlapping words).

16. In addition we find that Country Risk and Sentiment are quite persistent at the country level, with quarterly autoregressive coefficients of 0.922 and 0.933, respectively.

TABLE 4
Summary statistics

	Mean	Median	St. Dev.	Min	Max	N
PANEL A: FIRM-COUNTRY						
$CountryExposure_{i,c}$ *(std.)*	0.77	0.62	1.00	0.00	82.33	533,925
$\mathbb{1}(Headquarter)_{i,c}$	0.02	0.00	0.14	0.00	1.00	533,925
$\mathbb{1}(Exports)_{i,c}$	0.06	0.00	0.24	0.00	1.00	215,325
$\mathbb{1}(Subsidiaries)_{i,c}$	0.16	0.00	0.36	0.00	1.00	387,225
PANEL B: COUNTRY-QUARTER						
$CountryRisk_{c,t}^{ALL}$ *(std.)*	3.69	3.50	1.00	2.15	10.11	3,240
$CountryRisk_{c,t}^{NHQ}$ *(std.)*	4.22	4.04	1.00	2.57	11.84	3,240
$CountryRisk_{c,t}^{FIN}$ *(std.)*	3.87	3.70	1.00	2.16	11.72	3,240
$CountryRisk_{c,t}^{NFC}$ *(std.)*	3.33	3.12	1.00	1.93	9.89	3,240
$CountryRisk_{c,t}^{US}$ *(std.)*	3.16	2.98	1.00	1.93	10.06	3,240
$CountryRisk_{c,t}^{HQ}$ *(std.)*	0.57	0.24	1.00	0.00	12.27	2,838
$CountrySentiment_{c,t}^{ALL}$ *(std.)*	3.00	2.90	1.00	−0.46	7.40	3,240
$\overline{FirmRisk_{i,c,t}}_{c,t}$ *(std.)*	3.17	3.00	1.00	0.62	12.25	2,256
$Realized\ MSCI\ volatility_{c,t}$	0.10	0.09	0.06	0.02	1.16	2,961
$MSCI\ equity\ return_{c,t}$	0.02	0.03	0.10	−0.86	0.62	2,958
$Total\ inflows_{c,t}$ *(%)*	1.66	1.49	2.10	−17.67	20.33	2,936
$Sovereign\ CDS\ spread_{c,t}$ *(pct)*	1.87	0.74	3.92	0.01	29.01	2,713
$Real\ GDP\ growth_{c,t}$	0.93	1.05	5.89	−26.48	29.24	2,882
$\mathbb{1}(Stop\ episode\ for\ total\ flows_{c,t})$	0.13	0.00	0.34	0.00	1.00	2,734
$\mathbb{1}(Retrenchment\ episode\ for\ total\ flows_{c,t}$	0.13	0.00	0.33	0.00	1.00	2,734
$WUI_{c,t}$ *(std.)*	1.00	0.76	1.02	0.00	9.87	3,240

Notes: This table shows the mean, median, standard deviation, minimum, maximum, and number of observations of all variables that are used in the subsequent regression analyses. Panels A and B show the relevant statistics for the regression sample at the firm-country and country-quarter unit of analysis, respectively. In Panel A, $CountryExposure_{i,c}$ *(std.)* is the average over time of firm i's Country Exposure to country c, normalized by the standard deviation; and $\mathbb{1}(Headquarter)_{i,c}$, $\mathbb{1}(Exports)_{i,c}$, $\mathbb{1}(Subsidiaries)_{i,c}$ are binary variables equal to one if firm i is headquartered in country c, reports sales at any point between 2002 2017 to country c, or has at least one subsidiary in country c, respectively. In Panel B, $CountryRisk_{c,t}^{ALL}$ *(std.)* is the average for country c and quarter t of the Country Risk perceived by all firms as measured in their earnings call transcripts, normalized by the standard deviation in the panel; $CountryRisk_{c,t}^{NHQ}$ *(std.)*, $CountryRisk_{c,t}^{FIN}$ *(std.)*, $CountryRisk_{c,t}^{NFC}$ *(std.)*, $CountryRisk_{c,t}^{US}$ *(std.)*, and $CountryRisk_{c,t}^{HQ}$ *(std.)* are the same but based on firms not headquartered in c at t, financial (SIC $\in$ [6000, 6800)), non-financial (SIC $\notin$ [6000, 6800)), U.S.-based, and domestic firms, respectively; $CountrySentiment_{c,t}^{ALL}$ *(std.)* is the average for country c and quarter t of Country Sentiment perceived by all firms, normalized by the standard deviation in the panel; $\overline{FirmRisk_{i,t}}_{c,t}$ *(std.)* is the average over all firms headquartered in country c and quarter t of risk words per word mentioned by the firm during its earnings call (restricted to countries for which we have at least five firms), normalized by the standard deviation in the panel; $Realized\ MSCI\ volatility_{c,t}$ is the standard deviation of the daily MSCI stock return for country c during quarter t (based on local currency), $MSCI\ equity\ return_{c,t}$ is the $t-1$ to t change in log of the quarter-average MSCI stock return index (based on local currency) for country c and quarter t; $Total\ inflows_{c,t}$ *(%)* are inflows of equity and debt to country c during quarter t relative to the country's stock of capital in the previous quarter; $Sovereign\ CDS\ spread_{c,t}$ is the end-of-quarter 5-year sovereign CDS spread of country c and quarter t (in per cent); $Real\ GDP\ growth_{c,t}$ is the quarter-to-quarter per cent change in real GDP of country c and quarter t; $\mathbb{1}(Stop\ episode\ for\ total\ flows_{c,t})$ and $\mathbb{1}(Retrenchment\ episode\ for\ total\ flows_{c,t}$ are taken from Forbes and Warnock (2021) and are binary variables equal to one if there is a sudden stop and retrenchment episode, respectively; and $WUI_{c,t}$ *(std.)* is the World Uncertainty Index from Ahir *et al.* (2018), standardized by its own standard deviation in the panel. See also Appendix Table 8 for details on the construction of the variables.

indeed effectively separate variation in the two moments. A 1% increase in Country Risk is associated with a 0.103 (s.e. = 0.023) percentage point increase in realized volatility. To summarize,

TABLE 5

Country risk, country sentiment, and asset prices

	MSCI equity return$_{c,t}$		Δ*CDS spread$_{c,t}$*		Δ*Realized volatility$_{c,t}$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ log(*CountryRisk$^{ALL}_{c,t}$ (std.)*)	-0.399^{***}	-0.213^{***}	3.926^{***}	2.768^{***}	0.098^{***}	0.103^{***}
	(0.045)	(0.035)	(1.014)	(0.805)	(0.018)	(0.023)
Δ*IHS*(*CountrySentiment$^{ALL}_{c,t}$ (std.)*)		0.267^{***}		-1.456^{***}		0.008
		(0.050)		(0.515)		(0.011)
R^2	0.099	0.230	0.057	0.081	0.015	0.016
N	2,918	2,918	2,626	2,626	2,917	2,917

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. *IHS*($\cdot$) denotes the inverse hyperbolic sine transformation. All variables are as defined in Table 4; their construction is detailed in Appendix Table 8. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

our validation shows that countries' stock prices drop and become more volatile when they are perceived to become riskier, and their CDS spreads widen.

2. SOURCES OF COUNTRY RISK

Having validated our measures, we next systematically identify spikes ("crises") and demonstrate how we can use the underlying text to identify to what events managers and investors attribute these spikes in country risk.

Figure 2 shows the time series of Greek Country Risk as an example. The top line shows the average for Greek Country Risk using all firms in our sample, while the yellow-shaded area shows only the part of the variation accounted for by financial firms, with the grey-shaded region capturing the variation from non-financial firms. Aside from the Global Financial Crisis of 2008–2009 and the Coronavirus pandemic of 2020 (which, as we will show below, feature in all of our Country Risk graphs), the series shows three clear Greece-specific peaks, each attributable to key episodes in the Greek sovereign debt crisis. The first begins with the initial realization in the second quarter of 2010 that Greece had misreported its debts and that foreign banks were significantly exposed to a potential Greek default. The second peak coincides with the second bailout and imposition of a haircut for private holders of Greek debt in the fourth quarter of 2011; and the third is driven by concerns about Syriza's referendum and the possibility of a Greek exit from the European Monetary Union. To arrive at this interpretation, we systematically read the 30 snippets of text with the highest $\omega(b, \text{"}Greece\text{"})$ from the 100 transcripts with the highest level of $CountryRisk_{i,Greece,t}$ in the quarter in question and highlight the common theme in these conversations. Below the graph, we show two examples of text for each of the three episodes. As might be expected given the nature of these crises, much of the increase in perceived Greek risk is driven by financial firms during each of these episodes.

We find similar success in Figure 3, where we turn to Thailand as our second example. In this case, we see the major spikes in Thai risk come from the GFC, the severe flooding in late 2011, the military coup in the third quarter of 2014, and the Coronavirus pandemic. Comparing the grey- and yellow-shaded areas shows that the political crisis surrounding the attempted coup caused relatively more concern among non-financial firms than financial firms—in sharp contrast with patterns we saw during the consecutive Greek sovereign debt crises. We also see this in the high-impact snippets reported below the table. In contrast to the Greek snippets, where financial

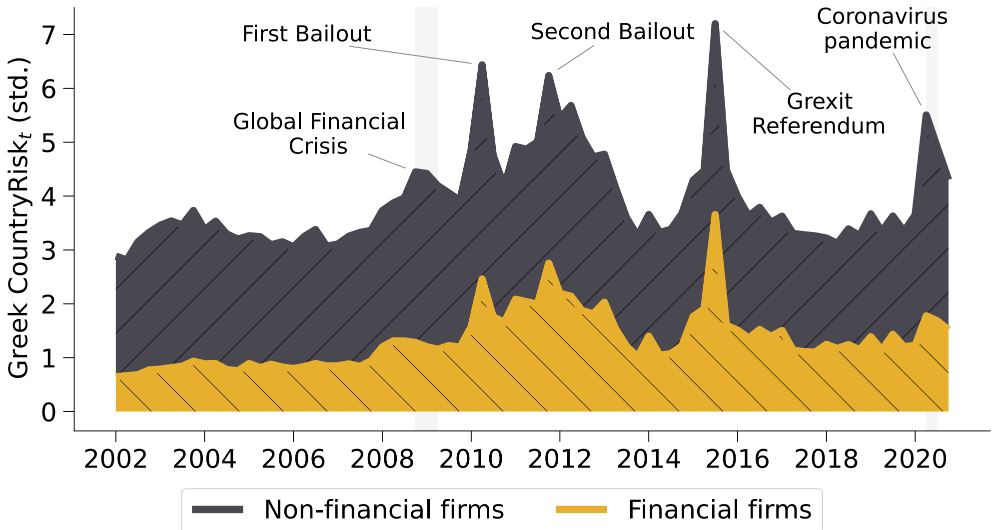


FIGURE 2
Sources of Greek country risk

Notes: This figure plots the time series of Greek $CountryRisk_{c,t}$ as defined in equation (5) but decomposed into Country Risk as perceived by non-financial and financial firms, respectively. The latter are firms whose four-digit SIC code is in 6000−6800. The text excerpts are selected from the highest-ranking snippets among all snippets from the top thirty highest-ranked firms when sorted on Country Risk for Greece

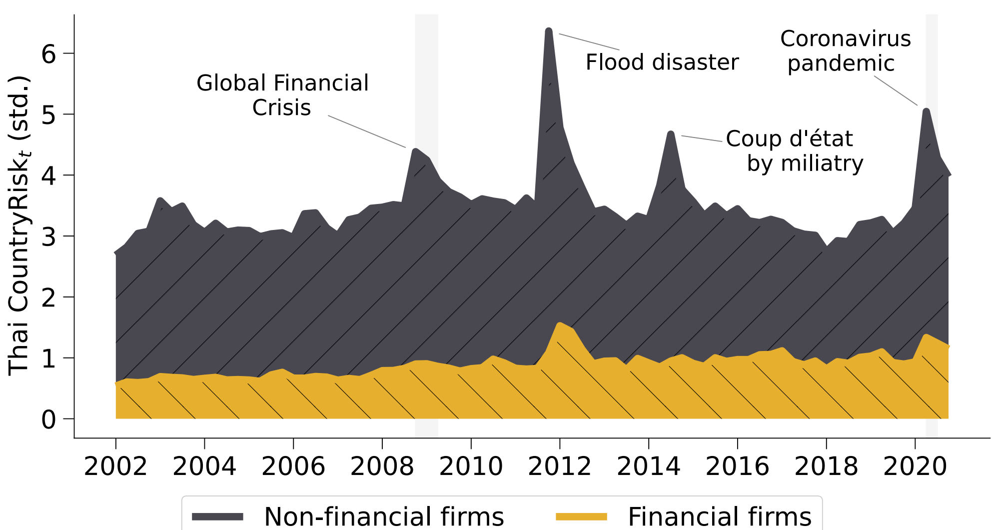


FIGURE 3
Sources of Thai country risk

Notes: This figure plots the time series of Thai $CountryRisk_{c,t}$ as defined in equation (5) but decomposed into Country Risk as perceived by non-financial and financial firms, respectively. The latter are firms whose four-digit SIC code is in 6000−6800. The text excerpts are selected from the highest-ranking snippets among all snippets from the top thirty highest-ranked firms when sorted on Country Risk for Thailand

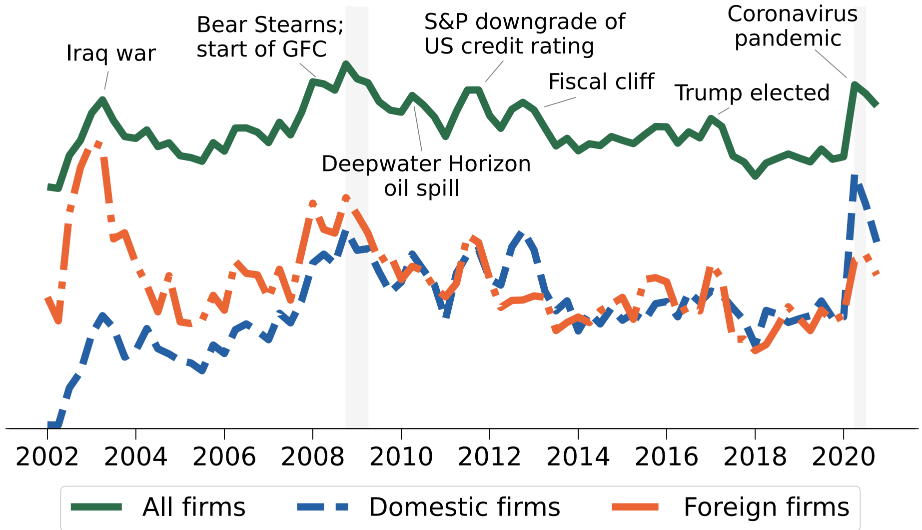


FIGURE 4

Sources and perceptions of U.S.' country risk

Notes: This figure plots the time series of U.S. $CountryRisk_{c,t}$ as defined in equation (5), decomposed into Country Risk as perceived by all, domestic, and foreign firms, respectively. The text excerpts are selected from the highest-ranking snippets among all snippets from the top thirty highest-ranked firms when sorted on Country Risk for the U.S.

firms discuss the effects of the Greek crises on financial markets, here we see non-financial corporates discuss the risk of supply chain disruption.

As our third example, we examine the U.S. in Figure 4. The U.S. occupies a unique position in our dataset as approximately half of our sample firms are based in the U.S. Therefore, for the U.S., it is particularly informative to decompose aggregate Country Risk, $CountryRisk^{ALL}_{USA,t}$ into U.S. risk perceived by American firms, $CountryRisk^{HQ}_{USA,t}$, and the U.S. risk perceived by non-American firms, $CountryRisk^{NHQ}_{USA,t}$. Again using our systematic reading of high-impact text snippets, the figure labels a number of spikes in U.S. risk. Most notably we see firms discussing risks associated with the Iraq War, the GFC, the Deepwater Horizon oil spill, the fiscal cliff negotiations in late 2012, and the election of Donald Trump in 2016. While for most of these episodes, foreign and domestic perceptions of U.S. Country Risk moved in lockstep, in other instances the perceptions diverged. In particular, the Iraq War, and to a lesser extent the election of Donald Trump, saw a dramatic increase in foreigners' perceptions of U.S. Country Risk, with the increase coming from American firms far more muted. By contrast, the concern around the Fiscal Cliff was far more concentrated in American firms. We make more systematic use of this kind of divergence in risk perceptions in our econometric analysis below.

Global and local crises

We now use our Country Risk measures to examine the recent history of each of the forty-five countries in our sample. To structure our analysis we find it useful to (a) use a standardized definition of when a country or a set of countries is in a "crisis", as perceived by global investors and executives; and (b) distinguish between global and country-specific "crises." In particular, we define a global or local "crisis" to be a spike in the relevant time series that is larger than two standard deviations above the sample mean (after projecting on country-fixed effects). While the

FIGURE 5

Time series of $GlobalRisk_t$

Notes: This figure shows the time series of $GlobalRisk_t$ defined as the mean of $CountryRisk_{c,t}$. Marked in grey are the quarters above two standard deviations (the red horizontal dashed line), which we define as global crises. The coefficients are standardized to have mean zero and standard deviation one for 2002q1–2019q4. NBER-based recession quarters are shaded in grey

threshold of two standard deviations is clearly arbitrary, it is a natural starting point; moreover, it is straightforward for future users of the data to change this threshold according to their specific research question or policy objective.

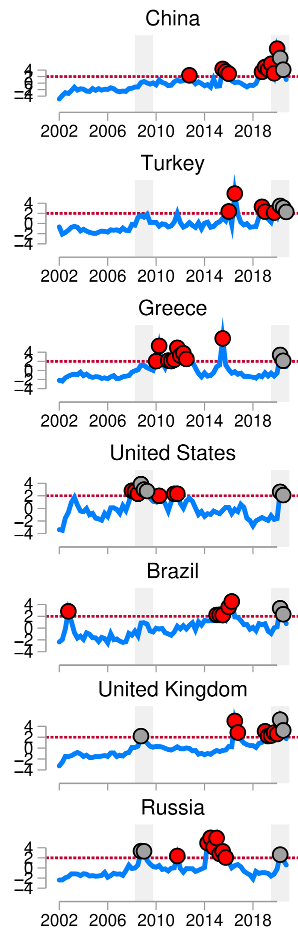
In order to identify global crises, we use our measure of Global Risk, which is calculated as the mean of Country Risk across our forty-five countries. Figure 5 plots Global Risk as the solid blue line. A number of features of Global Risk are immediately apparent. First, there are two major spikes: the GFC and the recent global pandemic. In addition, the Great Moderation (*e.g.* Bernanke, 2004; Galí and Gambetti, 2009) is clearly visible in the time series, with Global Risk from 2002–2006 lower than the entire period since the GFC. Moreover, the graph also shows a spike in 2011q4 during the height of the European sovereign debt crisis. Figure 5 also plots the line of two standard deviations above the sample mean (the dashed red line) and its associated global "crises" (marked with grey dots). Accordingly, the two global crises that we identify are the GFC during 2008q4–2009q2 and the recent global pandemic during 2020q2–2020q4 (with the European crisis remaining slightly below this threshold).

We next turn to identifying country-specific crises. Using our aforementioned threshold of two standard deviations, we consider a country to be in a local crisis when its perceived level of Country Risk is at least two full sample standard deviations above its country-specific mean. We additionally require the quarter to not also be a global crisis. Thus if a quarter in a country's time series satisfies those two conditions, we mark it with a red dot in the country's graph. For each of these episodes, we once again systematically read the snippets of text with the highest $\omega(b, c)$, and label the episode to summarize firms' predominant concerns at the time.

In Figure 6, we plot the aggregate time series of Country Risk of the twenty countries that have at least one local crisis according to our definition, with the ordering reflecting the number of country-specific crises. Appendix Figure 4 reports the equivalent graphs for all remaining countries that do not have a local crisis.[17] In addition to identifying crises at the country level (Column 1) and summarizing the predominant source of risk during each episode (Column 2),

17. We also consider countries as having no local crises if its only crises immediately follow a global crisis and firms' concerns during that spike in measured country risk are congruent with either the GFC or the coronavirus pandemic.

	Source	Transmission
China		
2012q4	Risk of ‘hard landing’	
2015q3-16q1	Equity market volatility	
2018q4-19q4	US-China trade war	NFC
2020q1	Start of Coronavirus outbreak	NFC
Turkey		
2016q1	FX volatility	
2016q3	Failed coup attempt	I
2018q4-19q1	Currency and debt crisis	FIN
2019q4	FX volatility	I
Greece		
2010q1-10q2	Sovereign debt crisis, first bailout	FIN
2011q1-12q3	Sovereign debt crisis, second bailout	FIN
2015q3	Grexit referendum, third bailout	FIN
United States		
2008q1-08q3	Lehman, start of GFC	FIN, I
2010q2	Deepwater Horizon oil spill	
2011q3-q4	S&P downgrade	
Brazil		
2002q4	Lula election	
2015q1-16q2	Corruption scandal	NFC
Great Britain		
2016q3-q4	Brexit referendum	FIN
2019q1-20q1	Lead-up to Brexit	
Russia		
2011q4	Economic uncertainty	
2014q2-15q4	Crimean crisis	NFC



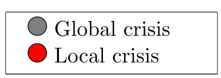
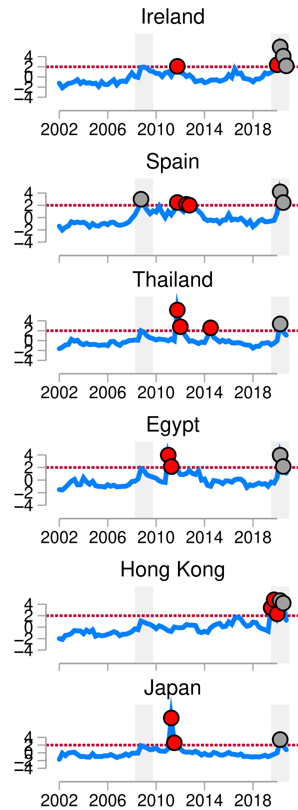


FIGURE 6

For caption see next page.

the figure in Column 3 summarizes the pattern of transmission of each crisis to foreign firms. In particular, the label “FIN” denotes disproportional transmission to foreign financial firms, while “NFC” indicates disproportional transmission to foreign non-financial corporates. The indicator “I” denotes crises with a particularly “irregular” transmission pattern. We discuss these classifications in detail in Section 3.

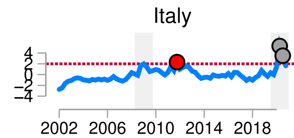
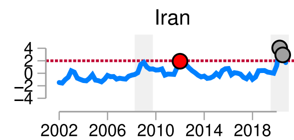
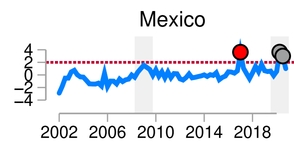
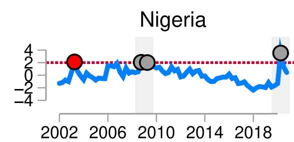
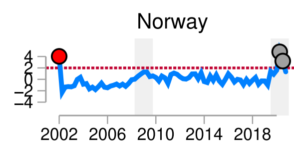
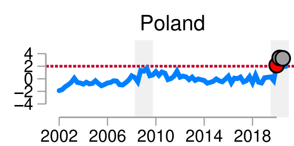
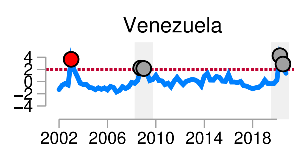
Where and when	Source	Transmission
Ireland		
2011q4	Sovereign debt crisis	FIN
2020q1	Brexit	
Spain		
2011q4	Sovereign debt crisis	FIN
2012q3-12q4	Sovereign debt crisis and bailout	
Thailand		
2011q4-12q1	Flood disaster	
2014q3	Military coup	
Egypt		
2011q1-11q2	Egyptian revolution	
Hong Kong		
2019q3-20q1	Protests against extradition bill	
Japan		
2011q2-q3	Fukushima disaster	I



Global crisis
Local crisis

FIGURE 6

For caption see next page.

Where and when	Source	Transmission	
Italy 2011q4	European sovereign debt crisis	FIN	
Iran 2012q1	Green Revolution	I	
Mexico 2017q1	Trump; trade risks		
Nigeria 2003q2	Oil workers' strike	I	
Norway 2002q1	Cooccurrence of local concerns		
Poland 2020q1	Coocurrence of local concerns		
Venezuela 2003q1	Aftermath of oil strike	NFC, I	

Global crisis
Local crisis

FIGURE 6
Country risk, crises, and patterns of transmission

Notes: This table describes and plots country crises based on $CountryRisk_{c,t}$ for the country indicated in Column 1. A global crisis (grey dots in the figures) is defined as $GlobalRisk_t$ being above two standard deviations (see also Figure 5); a local crisis (red dots in the figures) is defined as the country's $CountryRisk_{c,t}$ being above two standard deviations in the panel (the red horizontal dashed line). Column 1 indicates the country and crisis. For Brazil, we assume that 2015q4, which is just below the threshold of two standard deviations, is nevertheless part of the crisis that started in 2015q1. Column 2 indicates the Source of crises. It is a description summarizing discussions of the top thirty highest-ranked firms when sorted on Country Risk in that quarter. Column 3 indicates the Transmission of crises: *I* is based on Column 3 of Table 7 and indicates that the Regularity of Transmission is in the lowest quartile; *NFC* and *FIN* are based on Column 4 of Table 7 and indicate a statistically significant difference in the transmission of risk from o to d for non-financial and financials, respectively

TABLE 6

Top five origins and destinations of transmission risk for selected countries

Firms headquartered in	Discuss risks from	Risks originating in	Transmit most to
U.S.	China	China	Hong Kong
	Canada		Singapore
	Mexico		Taiwan
	Japan		South Korea
	Brazil		Japan
China	Hong Kong	Greece	Belgium
	U.S.		Italy
	Japan		Spain
	Taiwan		France
	Singapore		Switzerland
Japan	China	Russia	Turkey
	Thailand		Italy
	U.S.		Netherlands
	Indonesia		Sweden
	Singapore		Germany
Germany	China	Brazil	Chile
	Russia		Spain
	U.S.		Mexico
	Spain		France
	Poland		Norway
U.K.	Ireland	Turkey	Greece
	China		Italy
	U.S.		Russia
	Australia		Netherlands
	Spain		Spain
India	China	U.K.	Ireland
	U.K.		Australia
	U.S.		France
	Brazil		Sweden
	South Africa		Spain
France	China	Argentina	Chile
	Brazil		Spain
	Spain		Mexico
	Italy		Brazil
	U.S.		Italy
Italy	Spain	Egypt	Greece
	Brazil		Turkey
	Russia		Italy
	Turkey		France
	China		Israel
Brazil	Argentina	Iran	Turkey
	China		Russia
	Colombia		South Africa
	Mexico		Greece
	Chile		South Korea

(continued)

TABLE 6
Continued

Firms headquartered in	discuss risks from	Risks originating in	transmit most to
Canada	U.S.	Japan	South Korea
	China		Hong Kong
	Mexico		Israel
	Australia		Singapore
	U.K.		Switzerland

Notes: This table lists the ten largest economies in which firms in our sample are headquartered (Column 1), the top five countries those firms discuss risks about (Column 2); it also lists ten selected countries that firms perceive risk in about (Column 3), the top five countries those firms are headquartered in (Column 4). For additional countries, see Appendix Table 3. The rankings in Columns 2 and 4 are based on an appropriate sorting of $\overline{TransmissionRisk_{o\to d,t}}_{o\to d} = \frac{1}{T_{o,d}}\sum_t TransmissionRisk_{o\to d,t}$ by o for a given d (Column 2) or by d for a given o (Column 4). In Column 4, we exclude countries in which we have fewer than twenty-five firms headquartered, or countries that are not in our list of forty-five countries for which we have measures of $CountryRisk_{c,t}$.

The figure shows a number of notable features. First, the time series for most countries shows clearly the impact of the two global crises, although there is also substantial country-specific variation. Second, for all but two of these crises, a clear narrative emerges from reading the discussions between executives and investors, so that we are able to label the episodes. As expected, many of the countries with the largest number of local crises are emerging markets. The time series for China shows four crisis episodes. The first two in 2012 and 2015–16 both centre on the risk of lower growth and financial volatility. These are followed in 2018–19 by the escalating U.S.–China trade war. The final crisis, in the first quarter of 2020 captures the onset of the Coronavirus pandemic (which becomes a global crisis in the second quarter according to our definition). Brazil records its first crisis in 2002 during the turmoil leading up to the election of Lula da Silva, as well as a long period of upheaval surrounding the corruption scandals and recession of 2015–16. Great Britain records consecutive crises associated with the Brexit referendum, and then the possibility (and later execution) of a hard Brexit. Russia shows an economic crisis in 2011 and a long period of uncertainty surrounding the Crimean invasion in 2014–15, and the concurrent sanctions and depreciation of the ruble. Other headline-grabbing episodes picked up by our measures of country risk include the Hong Kong protests of 2019–20, the European sovereign debt crisis, Middle East wars, the Egyptian revolution of 2011, and the Fukushima disaster in Japan.

Aside from these prominent episodes, we record two episodes (Norway and Poland), where firms discuss local risks that are not tied to a single event at all. We label these instances “co-occurrence of local concerns”, where for example for Poland in 2020q1, Banca Comerical Portugues SA discusses higher capital charges related to currency risk, Stock Spirits Group PLC worries about the possibility of an alcohol excise tax, and UNIQA Insurance Group AG lament the “fluctuating” competitive environment in Poland. Such seemingly random co-occurrences are of course more likely to sway measured Country Risk for smaller countries that have relatively fewer international firms doing business there.

Third, although none of the firms in our sample are based in Iran, and only two in Venezuela, we are nevertheless able to measure meaningful variation in (commercially relevant) risk emanating from these countries, because some of our sample firms maintained commercial interests in these countries. The first of these is the 2003 oil strike in Venezuela and the second is the failed

TABLE 7
Crisis transmission patterns

	Global Impact $\widehat{y}$	Bilateral Transmission $\widehat{\beta}_{o,\tau}$	Regularity of Transmission R^2	Financial Transmission $\widehat{\alpha}^{FIN}_{o,\tau}/\widehat{\alpha}_{o,\tau}$
China: Start of Coronavirus outbreak (2020q1)	3.69	2.58^{***}	0.905	-0.89^{***}
U.S.: Lehman; start of GFC (2008q1–08q3)	2.27	0.92	0.554	2.70^{**}
Japan: Fukushima disaster (2011q2–11q3)	2.12	1.91^{*}	0.281	−0.06
China: U.S.–China trade war (2018q4–19q4)	2.08	1.73^{***}	0.924	-1.03^{***}
China: Equity market volatility (2015q3–16q1)	1.84	1.91^{***}	0.938	0.06
U.S.: S&P downgrade (2011q3–11q4)	1.75	1.01	0.762	0.39
U.S.: Deepwater Horizon oil spill (2010q2)	1.63	0.93	0.673	−0.98
China: Risk of 'hard landing' (2012q4)	1.55	1.41^{***}	0.964	−0.68
Greece: Grexit referendum (2015q3)	1.50	2.82^{***}	0.712	4.90^{***}
Mexico: Trump; trade risks (2017q1)	1.44	1.45^{***}	0.793	−0.48
Thailand: Flood disaster (2011q4–12q1)	1.40	4.00^{***}	0.683	0.23
Turkey: Failed coup attempt (2016q3)	1.39	1.44^{*}	0.467	0.33
U.K.: Brexit referendum (2016q3-16q4)	1.38	1.51^{***}	0.857	1.44^{***}
Russia: Crimean crisis (2014q2-15q4)	1.35	2.68^{***}	0.881	-0.47^{*}
Brazil: Corruption scandal (2015q1-16q2)	1.29	1.68^{***}	0.915	-0.89^{**}
Venezuela: Aftermath of oil strike (2003q1)	1.18	5.09^{*}	0.304	−0.88
Greece: First bailout (2010q1-10q2)	1.17	2.80^{***}	0.734	2.83^{***}
Turkey: Currency and debt crisis (2018q4-19q1)	1.16	1.79^{***}	0.628	2.10^{*}
U.K.: Lead-up to Brexit (2019q1-20q1)	1.14	1.17^{**}	0.855	−0.22
Thailand: Military coup (2014q3)	1.02	1.79^{***}	0.856	−1.04
Nigeria: Oil workers' strike (2003q2)	1.02	1.95	0.380	−0.95
Russia: Economic uncertainty (2011q4)	1.01	1.42^{***}	0.822	−0.51
Greece: Second bailout (2011q1-12q3)	1.00	3.13^{***}	0.722	7.73^{***}
Turkey: FX volatility (2019q4)	0.98	0.97	0.502	−1.22

(continued)

TABLE 7
Continued

	Global Impact $\widehat{y}$	Bilateral Transmission $\widehat{\beta}_{o,\tau}$	Regularity of Transmission R^2	Financial Transmission $\widehat{\alpha}^{FIN}_{o,\tau}/\widehat{\alpha}_{o,\tau}$
Spain: Sovereign debt crisis (2011q4)	0.97	1.55***	0.906	2.24**
Ireland: Brexit (2020q1)	0.97	0.98	0.751	−0.15
Spain: Bailout (2012q3-12q4)	0.97	1.67***	0.884	1.14
Turkey: FX volatility (2016q1)	0.96	1.08	0.603	−0.28
Egypt: Egyptian revolution (2011q1-11q2)	0.92	3.49***	0.902	0.11
Ireland: Sovereign debt crisis (2011q4)	0.90	1.10	0.874	11.85***
Hong Kong: Protests against extradition bill (2019q3-19q4)	0.86	1.49***	0.938	0.79
Italy: Sovereign debt crisis (2011q4)	0.81	1.26***	0.894	3.32***
Iran: Green Revolution (2012q1)	0.80	1.21	0.579	−0.96

Notes: This table lists four characteristics of each local crisis defined in Figure 6: Global Impact, Bilateral Transmission, Regularity of Transmission, and Financial Transmission. The first three characteristics are based on a regression of $TransmissionRisk_{o\to d,\tau}$ on $\overline{TransmissionRisk}_{o\to d,t\notin S^o}$ as defined in equation (8). Global Impact is the predicted value of $TransmissionRisk_{o\to d,\tau}$ for the country with the median of Transmission Risk, $\overline{TransmissionRisk_{o\to d,t\notin S^o}}^{median}$, using the estimated coefficients from the regression; Bilateral Transmission is the estimated coefficient on $\overline{TransmissionRisk}_{o\to d,t\notin S^o}$, $\widehat{\beta}_{o,\tau}$, with ***, **, and * denoting the statistical significance of $\widehat{\beta}_{o,\tau}$ being different from *one*; and Regularity of Transmission is the R^2 of the regression. We exclude origin-destination-crises that contain fewer than 10 firms from the regressions. Financial Transmission is the ratio of $\widehat{\alpha}^{FIN}_{o,\tau}/\widehat{\alpha}_{o,\tau}$ from a firm-level regression of $CountryRisk_{i,o,\tau} - \overline{CountryRisk}_{i,o,t\notin S^o}$ on a constant, $\widehat{\alpha}_{o,\tau}$, and an indicator equal to one if the firm is a financial firm, $\widehat{\alpha}^{FIN}_{o,\tau}$, with ***, **, and * denoting the statistical significance of $\widehat{\alpha}^{FIN}_{o,\tau}$ being different from zero. Norway 2002Q1 and Poland 2020Q1 are excluded because we did not identify a unified source for the crisis and Brazil 2002q4 is excluded due to the limited country coverage prior to 2003.

Iranian Green Revolution of 2012.[18] These examples also highlight an important feature of our approach: because we rely on discussions at globally listed firms, all of our measures will only be sensitive to variation in risk that affects those global businesses. The less connected a country is to these businesses, the less sensitive we expect our measures to be to events in that country.

3. THE TRANSMISSION OF COUNTRY RISK

Having described the sources of aggregate variation in country risk, we now turn to understanding the pattern of transmission of risks around the world. We begin by examining the regular flow or risks from a given origin country to a given destination country, before examining how different types of crises deviate from this usual pattern.

18. At 1.82 standard deviations, Country Risk of Iran is just below our threshold of two standard deviations in 2012q1; however, because of its clear spike, we nevertheless include it in Figure 6.

3.1. *Regular transmission of country risk*

Table 6 lists the top origins and destinations of average Transmission Risk for a selection of countries,

$$\overline{TransmissionRisk}_{o\to d} = \sum_t \frac{1}{T} TransmissionRisk_{o\to d,t}.$$

From a cursory glance over the table, we can see that firms tend to worry more about risks originating in countries geographically closer to them. In addition, one can immediately see the importance of language and historical ties, with the U.K. worrying not only about nearby Ireland but also about Australia.[19] In Appendix Table 4 we confirm this conjecture more systematically. Building on a large literature in trade and international finance (Head and Mayer, 2014), we run a gravity regression of bilateral Transmission Risk with source and destination fixed effects. We find that distance, geographical contiguity, and a common language are all significant explanatory factors for the transmission of risk across countries.

To add texture to this analysis, Appendix Table 5 decomposes the aggregate flow of risk to the U.S. by showing the top five origins of transmission risk for ten sectors within the U.S. The table lists the firm in the S&P 500 with the largest transmission risk from each origin as an example. It shows a large degree of heterogeneity in the countries driving transmission to the U.S. by industry. For example, major source countries of transmission risk for firms in the U.S. technology sector are China, Japan, Canada, U.K., and Brazil; while firms in the U.S. energy sector are concerned with risks associated with Canada, Mexico, Nigeria, Saudi Arabia, and Brazil. Looking into the underlying conference call transcripts paints a rich picture of the commercial links underlying this variation. For example, Devon Energy's Canadian exposure stems from large holdings of local oil resources, while Conoco Philips is involved in litigation trying to claw back assets expropriated in Venezuela.

3.2. *Crisis transmission*

Next, we explore the extent to which these patterns of transmission change during crises to examine how these extreme events propagate around the world. We construct separate measures of $TransmissionRisk_{o\to d,\tau}$ for each of the crises listed in Figure 6. We then compare the pattern of transmission during each crisis with the usual pattern of transmission from that origin country by regressing the pattern of transmission during crisis τ in country o onto the usual pattern of transmission during non-crisis periods,

$$TransmissionRisk_{o\to d,\tau} = \alpha_{o,\tau} + \beta_{o,\tau}\overline{TransmissionRisk}_{o\to d,t\notin S^o} + \epsilon_{o\to d,\tau}, \qquad (8)$$

where S^o is the set of time periods during which origin country o is in crisis. Throughout, we weight each observation by the number of firms in country d.

We illustrate this approach with the help of six example plots shown in Figure 7 that summarize how each crisis is transmitted to foreign firms. To understand these figures, note first that the 45-degree line represents the usual transmission of risk during non-crisis periods. The farther above this line is a given destination country, the more concerned are the destination country's firms with risks emanating from the origin country during the crisis than normal. For ease of reference, we refer to the median predicted value from this projection as the crisis' "global impact"

19. Appendix Table 3 expands on this analysis by showing the top destinations of risk transmitted from the twenty largest economies in our sample.

(how much risk is transmitted to the median country?); and to the slope of the regression line as the degree of "bilateral transmission" (how much more concerned are countries that are traditionally concerned about the origin country?). Finally, the R^2 of the regression line measures the "regularlity" of transmission—the degree to which transmission during a given crisis follows the usual pattern of transmission during non-crisis periods.

Panels (a) and (b) of Figure 7 plot the two crises with the highest global impact in our sample. Panel (a) shows the start of the GFC—the transmission of risk from the U.S. to foreign firms in 2008. During the start of the GFC, all recipient countries are clearly above the 45-degree line, speaking to the significant impact this crisis had on countries around the world. Further, the GFC was a crisis with a high global impact (the second highest in our sample) affecting all countries regardless of their historical exposure to the U.S., but only moderate bilateral transmission (the fitted line is close to one). Moreover, in keeping with this global transmission pattern, the GFC also stands out for its high degree of irregular transmission (an R^2 of 0.55—much lower than most other crises in our sample). Panel (b) shows the same relationship for the beginning of the Coronavirus pandemic in China in the first quarter of 2020. It is the crisis with the highest global impact in our sample. All countries are again well above the 45-degree line, but now we also see a much larger degree of bilateral transmission to nearby countries: Hong Kong, Taiwan, and Singapore, reflecting the fact that many observers were expecting the pandemic to affect nearby Asian countries first.

Panels (c) and (d) plot the two crises with the strongest bilateral transmission patterns, the Thai floods of 2011–12 and the start of the Greek sovereign debt crisis in 2010. Turning first to Thailand, we see that the countries that experience the largest increase in Transmission Risk, Singapore and Japan, are the countries that are also most exposed to Thailand during non-crisis times. (The slope coefficient signals a 4.00 (s.e. = 0.49)-fold increase in risk transmission to these countries.) Following the same method we used to identify the sources of country risk, we can again read influential snippets of text associated with each observation in the plot. We see, for example, that Japanese firms discuss the supply chain disruptions emanating from the Thai floods. Countries generally less exposed to Thailand, by contrast, discuss risk propagating from the floods dramatically less (the bulk of observations cluster close to the 45-degree line). Similarly, looking at the pattern of risk transmission during the start of the Greek crisis in Panel (d), we see high levels of Transmission Risk to firms based in other Euro Area countries (increasing by a factor of 2.80 (s.e. = 0.32), yet little propagation to countries outside the Euro Area that are traditionally less exposed to Greece. This strongly local pattern of transmission is in stark contrast to the much more global transmission pattern at the start of the GFC in Panel (a).

Panels (e) and (f) of Figure 7 plot the pattern of transmission risk for the Hong Kong Protests and the Fukushima Nuclear Disaster, the crises with the highest and lowest R^2 in our sample, respectively. In the case of Hong Kong, one sees a tight fit around the regression line (with an R^2 of 0.94). Countries generally most exposed to Hong Kong, such as Singapore, Malaysia, China, and Taiwan, see large increases in risk, with other countries such as the U.S., seeing relatively small increases. We contrast this regular transmission with Fukushima in Panel (f), the crisis with the lowest R^2 in our sample (0.28).[20] The plot shows large dispersion and unusually large impacts in Germany, among others. Systematically examining high-impact snippets of text from German firms reveals the reason: the Fukushima disaster precipitated a political drive to end nuclear power in Germany, and thus threatened the viability of an entire industry in this faraway location, including that of firms that have no observable commercial links with Japan

20. For a detailed analysis of this event also see Boehm *et al.* (2019) and Carvalho *et al.* (2021).

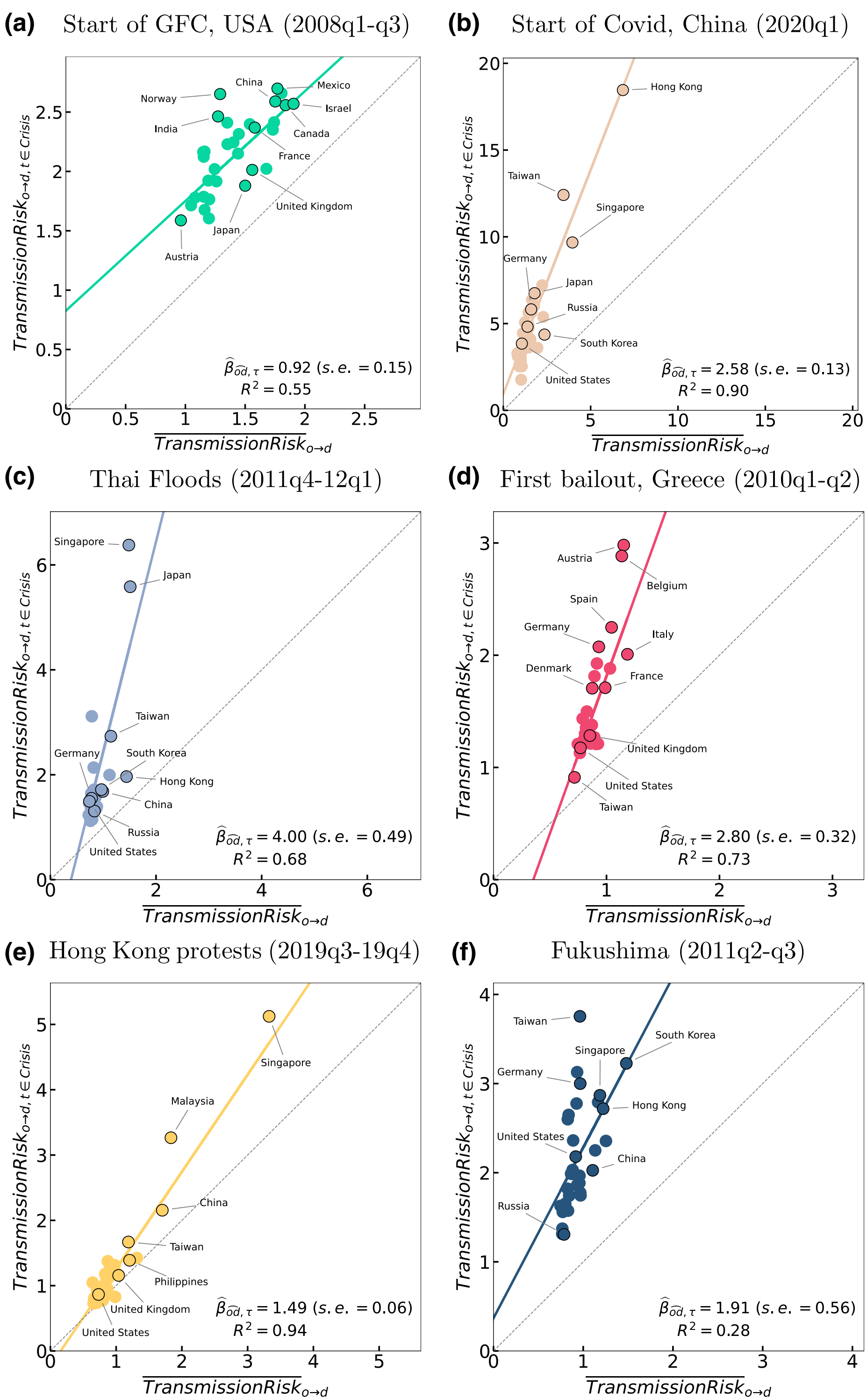


FIGURE 7

Patterns of transmission during major crises

Notes: This figure plots six different crises, each in one panel, $TransmissionRisk_{o\to d,\tau}$ against $\overline{TransmissionRisk}_{o\to d,t\notin S^o}$, the fitted regression line from a linear regression as defined in equation (8), and the 45-degree line (in grey). The crises are selected from Table 7 and the fitted regression line corresponds to the regression on which the values reported in that table are based on

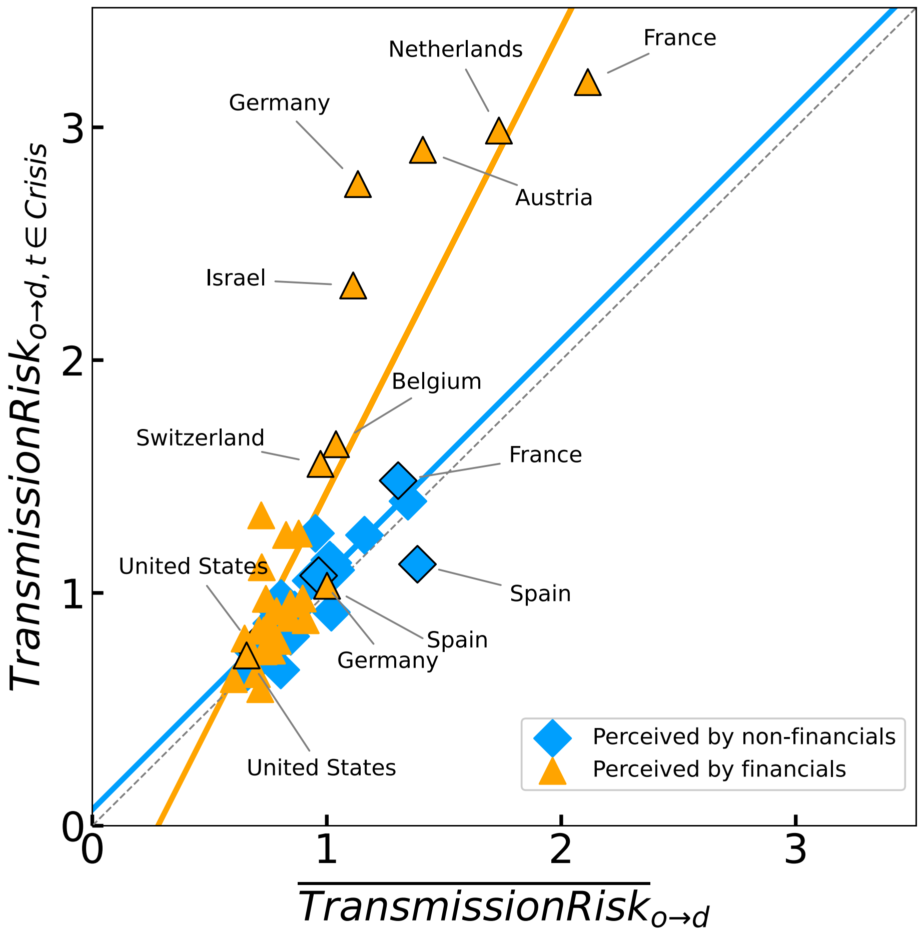


FIGURE 8

Italy: European sovereign debt crisis (2011q4)

Notes: This figure plots two set of firms, financials and non-financials, $TransmissionRisk_{o\to d,\tau}$ against $\overline{TransmissionRisk}_{o\to d,t\notin S^o}$, the fitted regression line from a linear regression as defined in equation (8), and the 45-degree line (in grey). The crisis is selected from Table 7

whatsoever. Other outliers are attributable to the unusual effects this event had on supply chains, fishing, and the insurance industry, among others.

Financial Transmission. Having illustrated these major features of the pattern of transmission, Figure 8 goes one step further by plotting separately transmission to financial (triangles) and non-financial firms (squares) for the case of the Italian sovereign debt crisis of 2011. The Figure clearly shows that, in this instance, the transmission of Italian risk to foreign countries operated almost exclusively through financial firms (the triangles are far above the 45-degree line, while the squares are not).

To examine the degree of financial transmission more systematically, we run a firm-level regression where the dependent variable is the Country Risk that foreign firm i perceives from origin country o during crisis τ, relative to the average risk that same firm perceives from that country during non-crisis times ($t\notin S^o$), along with a dummy variable indicating whether that particular firm is in the financial industry:

$$CountryRisk_{i,o,\tau} - \overline{CountryRisk}_{i,o,t\notin S^o} = \alpha_{o,\tau} + \alpha^{Fin}_{o,\tau}\mathbb{1}_{Fin(i)} + \epsilon_{o\to i,\tau}. \tag{9}$$

If $\alpha^{Fin}_{o,\tau}$ is positive, this means that during the crisis in question, financial firms perceived a larger increase in risk from country o than did non-financial firms. For example, for the Italian sovereign debt crisis shown above, we find a large and highly significant $\alpha^{Fin}_{o,\tau}$.

Transmission Patterns. Table 7 provides a concise summary of all patterns introduced in this subsection. In particular, it lists for each of our local crises, the degree of financial transmission from specification (9), along with the three other features of crisis transmission from specification (8) outlined above. The table facilitates an easy comparison of the transmission pattern across the different crisis episodes in our sample.

For each crisis, Column 1 shows its global impact (the predicted impact on the median country, normalized with the (panel) standard deviation of country risk). Immediately, we can see that the measure delivers an intuitive ranking, with—as mentioned before—the start of the Coronavirus outbreak in 2020q1 in China ranked as the crisis with the largest global impact followed by the start of the GFC in the U.S. from 2008q1 to 2008q3. While large countries dominate the top of the rankings (with Japan, China, and the U.S. occupying the top eight spots), we see the Greek sovereign debt crisis, Mexican trade war, Thai floods, Turkish coup, and Brexit follow. Crises with relatively low levels of global impact are the Green Revolution in Iran, and the echoes of Brexit and the European Sovereign debt crisis in Ireland, Italy, and Spain. Column 2 shows the degree of bilateral transmission. Because a coefficient of one indicates an unchanged pattern of transmission relative to normal times, asterisks mark slope coefficients that are statistically significantly different than this benchmark (one rather than zero). We find that most of the crises in our sample feature significantly higher bilateral transmission than during non-crisis times—with significantly more severe transmission to traditionally exposed countries.[21] Column 3 gives the regularity of transmission (the R^2 of specification (8)); and Column 4 reports the relative financial transmission as the ratio of $\alpha^{Fin}_{o,\tau}/\alpha_{o,\tau}$ from specification (9), which measures the degree of transmission to foreign financial firms relative to the non-financial corporate sector. Asterisks indicate crises where $\alpha^{Fin}_{o,\tau}$ is statistically distinguishable from zero (either positive or negative).[22]

Overall, Table 7 shows a large degree of heterogeneity across crises, even when reducing our data to these four key indicators. To elicit these general patterns more systematically, we manually classify crises into four (possibly overlapping) groups: Developed Market crises, Natural Disasters, Sovereign Debt crises, and Political Instability, using the sources of each crisis as listed in Figure 6 as a guide. In Appendix Table 6, we then regress our four transmission indicators from Table 7 on dummies for these four different types of crises. A number of general patterns emerge. First, in Column 1, we see that crises originating in developed markets and those centring on sovereign debt propagate disproportionately to foreign financial firms. Second, crises in emerging markets tend to propagate more bilaterally (locally) than those originating in developed markets. Third, none of these features seems to predict the degree of regularity of the transmission. In this sense, it seems hard to predict what type of crisis will propagate regularly as opposed to irregularly.

21. Appendix Table 4 performs a related comparison. There, we separately explore the explanatory power of gravity variables for the transmission of country risk in non-crisis and crisis times. While we see that risk always transmits more to nearby countries and to those with a common language (gravity), the role of these variables increases significantly during crises. In this sense, gravity strengthens during crises, with disproportionately higher transmission to nearby countries during crisis times. This mirrors our finding that ($\beta_{o,\tau} > 1$) in the vast majority of crises listed in Table 7.

22. This test is also the basis for marking crises for disproportionate transmission to foreign financial firms ("FIN" in Figure 6 if positive and "NFC" if negative). Crises marked with an "I" in Figure 6 are those in the bottom quartile of Column 3 in Table 7.

4. COUNTRY RISK AND GLOBAL CAPITAL FLOWS

Having characterized the sources and transmission of country risk, we now apply our measures to explore the relationship between country risk and capital flows. A large literature going back to Calvo *et al.* (1996) studies the relative importance of push (*i.e.* global or source-country) factors and pull (*i.e.* recipient-country-specific) factors driving capital flows. Generally, the literature has found that capital flows contract in response to bad global news, but it has proven more difficult to identify variables that can account for country-specific variation in capital inflows.

Using our global and country-specific measures of risk, we are able to revisit this result. In Panel A of Table 8, we examine country risk as a driver of global capital flows. Column 1 shows a univariate regression of total capital inflows to a country scaled by the stock of foreign investment[23] on Global Risk (conditional on country-fixed effects). Consistent with the importance of push factors and the "fickleness" of capital flows (Caballero and Simsek, 2020), we find a negative and statistically significant effect: when global risk is high, capital flows dry up globally. When we include Country Risk in Column 2, the coefficient on Global Risk is attenuated, while the coefficient on Country Risk is negative and highly statistically significant: A one standard deviation increase in a country's risk is associated with 0.589 (s.e. = 0.186) percentage point drop in inflows—corresponding to a 36% reduction in inflows relative to the sample mean. In Column 3, we control for country-specific GDP growth, a traditional pull factor. Consistent with the findings in the existing literature, this additional variable remains insignificant. By contrast, we see that the coefficient on Country Risk remains largely unaffected and highly statistically significant. In Column 4, we introduce time fixed effects and see that the effect of Country Risk on capital inflows is essentially unchanged, even when we partially out all possible global variation in push factors. Column 5 adds Country Sentiment to the specification. As expected, we find that more positive news about a country (more positive sentiment) is associated with a significant increase in capital inflows (0.652, s.e. = 0.191). The coefficient on Country Risk is reduced by about half but remains negative and statistically significant at the 10% level (−0.304, s.e. = 0.173). Thus, both Country Risk and Country Sentiment can account for country-specific variation in capital flows, going beyond the global variation emphasized in the extant literature. When earnings call participants discuss a given country with a more positive tone, more capital flows into that country, whereas heightened perceptions of risks in a given country are associated with lower capital inflows.

Panel B repeats this analysis, but replaces our (continuous) measures of country and global risk with dummies corresponding to only the peaks in these series—local and global crises, as defined in Figure 6. Consistent with our findings above, we see that countries experiencing a local crisis on average experience a 1.439 (s.e. = 0.362) percentage point drop in their capital inflows relative to the existing stock of foreign holdings—an 87% reduction relative to the sample mean (Column 2). The same specification shows a similarly large drop in periods of global crisis (−1.705, s.e. = 0.243). In other words, in times of global and local crises, countries tend to experience significant episodes of foreign sales of their financial assets.

23. In our main specification, we measure total inflows as the sum of portfolio inflows, FDI inflows, and Other inflows from the Balance of Payments data. The outstanding stock of debt is defined equivalently using International Investment Position data. While we normalize capital flows by the outstanding stock for simplicity, Burger *et al.* (2019) demonstrate the strong explanatory power of lagged portfolio weights as a normalizing factor. Appendix Table 7 replicates these same specifications excluding FDI from our measure of capital inflows. Appendix Table 8 details the source of all variables used in this and all subsequent sections.

TABLE 8
Country risk and capital flows

	Total inflows$_{c,t}$ (%)				
PANEL A	(1)	(2)	(3)	(4)	(5)
$CountryRisk^{ALL}_{c,t}$ (std.)		-0.598^{***}	-0.583^{***}	-0.511^{***}	-0.304^{*}
		(0.186)	(0.183)	(0.136)	(0.173)
$GlobalRisk_t$ (std.)	-0.459^{***}	-0.267^{**}	-0.279^{**}		
	(0.074)	(0.099)	(0.103)		
Real GDP growth$_{c,t}$			-0.003	0.025^{***}	
			(0.007)	(0.009)	
$CountrySentiment^{ALL}_{c,t}$ (std.)					0.652^{***}
					(0.191)
R^2	0.122	0.132	0.137	0.275	0.269
N	2,936	2,936	2,796	2,796	2,936
	Total inflows$_{c,t}$ (%)				
PANEL B	(1)	(2)	(3)	(4)	
$\mathbb{1}(CountryCrisis_{c,t})$		-1.439^{***}	-1.381^{***}	-0.888^{***}	
		(0.362)	(0.340)	(0.300)	
$\mathbb{1}(GlobalCrisis_t)$	-1.671^{***}	-1.705^{***}	-1.830^{***}		
	(0.241)	(0.243)	(0.237)		
Real GDP growth$_{c,t}$			-0.003	0.026^{***}	
			(0.007)	(0.009)	
R^2	0.101	0.111	0.118	0.271	
N	2,936	2,936	2,796	2,796	
Country FE	yes	yes	yes	yes	yes
Time FE	no	no	no	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All other variables are defined as shown in Table 4. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

These findings resonate with a large literature studying "sudden stop" episodes in emerging and developed economies (Forbes and Warnock, 2012, 2021). A sudden stop is defined as a major reduction in gross foreign capital inflows, a phenomenon the literature has emphasized as a key feature of crises in emerging markets Mendoza (2010). To study how sudden stops relate to perceived country risk, Table 9, Panel A repeats our regressions of Table 8, but now replaces the dependent variable with a dummy that is equal to one if country c experiences a sudden stop in quarter t (as classified by Forbes and Warnock (2021)). We find a similar pattern as for total capital inflows, with increases in both Country Risk and decreases in Country Sentiment strongly associated with sudden stop episodes. For example, in Column 2, a one standard deviation increase in Country Risk is associated with a 8.2 percentage point increase in the (linear) probability that the country in question experiences a sudden stop. Building on these results, Panel B shows rises in Global Risk but not Country Risk are associated with "Retrenchment", episodes during which domestic investors liquidate large amounts of foreign investments and return the funds to their home countries (again, as defined by Forbes and Warnock (2021)).[24]

24. Much of this variation is again driven by global and local crises. Appendix Table 9 shows similar results using only the dummies for local and global crises.

TABLE 9
Country risk, sudden stops, and retrenchment

PANEL A	$\mathbb{1}$(*Stop episode for total flows*$_{c,t}$)				
	(1)	(2)	(3)	(4)	(5)
$CountryRisk^{ALL}_{c,t}$ *(std.)*		0.082**	0.079**	0.086**	0.060*
		(0.037)	(0.038)	(0.034)	(0.032)
$GlobalRisk_t$ *(std.)*	0.092***	0.066***	0.067***		
	(0.009)	(0.015)	(0.015)		
Real GDP growth$_{c,t}$			−0.001	0.000	
			(0.001)	(0.001)	
$CountrySentiment^{ALL}_{c,t}$ *(std.)*					−0.070**
					(0.028)
R^2	0.088	0.095	0.096	0.337	0.342
N	2,734	2,734	2,627	2,627	2,734
PANEL B	$\mathbb{1}$(*Retrenchment episode for total flows*$_{c,t}$)				
	(1)	(2)	(3)	(4)	(5)
$CountryRisk^{ALL}_{c,t}$ *(std.)*		0.009	0.007	0.012	−0.006
		(0.025)	(0.024)	(0.020)	(0.020)
$GlobalRisk_t$ *(std.)*	0.067***	0.064***	0.064***		
	(0.010)	(0.013)	(0.014)		
Real GDP growth$_{c,t}$			−0.001	0.000	
			(0.001)	(0.001)	
$CountrySentiment^{ALL}_{c,t}$ *(std.)*					−0.045
					(0.029)
R^2	0.053	0.053	0.053	0.264	0.262
N	2,734	2,734	2,627	2,627	2,734
Country FE	yes	yes	yes	yes	yes
Time FE	no	no	no	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. The outcome in Panel A, $\mathbb{1}$(*Stop episode for total flows*$_{c,t}$), is a dummy equal to one if there is a stop episode for total capital flows of country c in quarter t. The outcome in Panel B, $\mathbb{1}$(*Retrenchment episode for total flows*$_{c,t}$), is a dummy equal to one if there is a retrenchment period for total capital flows. Both outcomes are from Forbes and Warnock (2021). All other variables are defined as in Table 4. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Thus, while we see that both country-specific factors (Country Risk and Country Sentiment) and global factors (Global Risk) are significant drivers of capital inflows and sudden stops, it tends to be heightened Global Risk that account for episodes of domestic retrenchment.

Alternative measures of country risk

In Table 10, we unpack our aggregate Country Risk series to better understand the sources of its explanatory power. The first column of Panel A replicates our regression of capital inflows on Country Risk as perceived by all firms, $CountryRisk^{ALL}_{c,t}$ (this time without controlling for GDP growth, but with the full set of country and time fixed effects). Next, we instead include Country Risk as perceived by all firms headquartered in the U.S. We find that the point estimate increases slightly. The coefficient decreases when we instead look at the effect of Country Risk

TABLE 10
Capital flows and heterogeneous perceptions of country risk

PANEL A	*Total inflows$_{c,t}$ (%)*			
	(1)	(2)	(3)	(4)
$CountryRisk_{c,t}^{ALL}$ *(std.)*	-0.551^{***}			
	(0.145)			
$CountryRisk_{c,t}^{U.S.\ firms}$ *(std.)*		-0.781^{***}		
		(0.183)		
$CountryRisk_{c,t}^{NHQ}$ *(std.)*			-0.446^{***}	-0.423^{**}
			(0.160)	(0.162)
$WUI_{c,t}$ *(std.)*				-0.091^{*}
				(0.046)
R^2	0.260	0.259	0.258	0.260
N	2,936	2,936	2,936	2,936

PANEL B	*Total inflows$_{c,t}$(%)*			*Portfolio$_{c,t}$ (%)*
	(1)	(2)	(3)	(4)
$CountryRisk_{c,t}^{NHQ}$ *(std.)*	-0.430^{***}	-0.418^{***}		
	(0.159)	(0.144)		
$CountryRisk_{c,t}^{HQ}$ *(std.)*	0.065			
	(0.065)			
$\overline{\text{FirmRisk}_{i,t}}_{c,t}$ *(std.)*		-0.149^{**}		
		(0.067)		
$CountryRisk_{c,t}^{FIN}$ *(std.)*			-0.332^{***}	-1.109^{**}
			(0.116)	(0.424)
$CountryRisk_{c,t}^{NFC}$ *(std.)*			-0.261	0.006
			(0.166)	(0.260)
R^2	0.287	0.361	0.261	0.134
N	2,710	2,163	2,936	2,936
Country FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are defined as shown in Table 4. All regressions include country and year-quarter fixed effects. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

as perceived by foreign firms, $CountryRisk^{NHQ}$, but continues to be strongly statistically and economically significant. We conclude that the information content of these three broad alternative aggregations of country risk is largely similar.[25]

Column 4 compares the information content of Country Risk with that of the World Uncertainty Index (WUI) (Ahir *et al.*, 2018), a measure of uncertainty available for a much larger set of 143 countries. Rather than operating on firm-level texts, the WUI counts the frequency of synonyms of risk and uncertainty directly in the EIU Country Reports. While the WUI is weakly positively correlated with our measure of Country Risk (the average within-country correlation is 0.1 in levels, but effectively zero in changes), controlling for it in the regression changes the coefficient on $CountryRisk^{NHQ}$ only slightly. Appendix Tables 10 and 11 expand on this theme, comparing and contrasting the information content of Country Risk with that of both WUI and country-level indices of Economic Policy Uncertainty (EPU) (Baker *et al.*, 2016), which are

25. The correlations between the three measures are all above 92%.

available for twenty-two countries and measure specifically the part of country risk associated with economic policy. The average within-country correlation between these twenty-two EPU measures and $CountryRisk^{ALL}$ is 0.51 (0.24 in changes). Across specifications, we find that these alternative text-based measures also tend to correlate with capital inflows and CDS spreads with the predicted sign. However, the table also shows that Country Risk is more strongly associated with all of these outcomes. The reason for this better fit is likely twofold. First, both alternative text-based measures ultimately rely on the writings of journalists rather than on conversations between executives and investors at global firms, who may be more directly involved in decisions moving capital and investments. Second, both WUI and EPU are constructed by counting the frequency of mentions of risk (or economic policy uncertainty) in national publications, allocating risk based on who is writing the text (a newspaper in a given country and the analyst at EIU responsible for a country, respectively), whereas our procedure isolates explicitly which country the speaker associates a given risk with. In this sense, both alternative measures are conceptually more similar to $\overline{FirmRisk_{i,t}}_{c,t}$ (discussed below) than $CountryRisk_{c,t}$.

Heterogeneous perceptions of country risk

In Panel B of Table 10, we consider the differential explanatory power of heterogeneous risk perceptions.[26] Column 1 contrasts the explanatory power of Country Risk as perceived by the firms based in that particular country (*HQ*) and firms based in other, foreign, countries (*NHQ*). We see that the perceptions of domestic firms (*HQ*) are insignificant, demonstrating that, on average, the explanatory power for capital flows is coming from foreign rather than domestic risk perceptions. While it is possible that this pattern arises because perceptions of domestic firms are measured with more error than the perceptions of the more numerous foreign firms, it also suggests that foreigners' perceptions may be an important variable in and of itself—consistent with the widely held view among policymakers that foreigners' perceptions of a country's riskiness (particularly those of decision makers at global firms) are important drivers of capital flows.

In Column 2 we find similar results when instead proxying for domestic perceptions with the average number of times participants in earnings calls of firms headquartered in the country mention a synonym for risk or uncertainty, $\overline{FirmRisk_{i,t}}_{c,t} := (1/N)\sum_{i\in c(i)} FirmRisk_{i,t}$, where $FirmRisk_{i,t}$ is the normalized unconditional count of risk synonyms in firm i's earnings call during quarter t (Hassan *et al.*, 2019). This measure captures the total risk as perceived by firms based in the country, regardless of where this risk is coming from. Remarkably, adding this control again barely attenuates the coefficient on $CountryRisk^{NHQ}$. This finding shows clearly that our procedure of conditioning on which country executives and investors are talking about, rather than simply averaging mentions of risk by firms in a given country, is key for the informativeness of our measures.

In Columns 3 and 4, we consider the relative explanatory power of the risk perceptions of financial (*FIN*) and non-financial (*NFC*) firms, motivated by the literature on the Global Financial Cycle, where fluctuations in financial risk are argued to be the key driver of capital flows and asset prices. We find that both are strongly predictive of aggregate capital inflows, with the perceptions of financial firms having a stronger effect (albeit not statistically significantly so).[27] By contrast, in Column 4, we see that it is exclusively the perception of financial firms explaining portfolio inflows. These purchases of stocks and bonds are sometimes referred to as "hot money"

26. While we focus on exploring the relative explanatory power of different aggregations, one could instead imagine using the microdata to ask what combination of firm-level perceptions best explains or predicts capital flows, or other variables of interest.

27. We have 2,212 (SIC code in 6000 to 6800) and 10,114 non-financial firms in our sample.

as they are notoriously flighty (Edison and Reinhart, 2001) and by far the most volatile component of capital inflows. These estimates thus suggest that the perceptions of financial firms are particularly important in explaining this important component of capital flows.

Taken together, these results provide a more nuanced interpretation of the drivers of global capital flows than the canonical push-pull dichotomy. While we find very strong explanatory power coming from a country-specific variable, $CountryRisk_{c,t}$, it is a country-specific variable capturing the perceptions of global firms and executives, in particular, those at foreign and financial firms. In this sense, whether to think of it as a pull factor, because it is recipient country specific, or a push factor, because it is capturing the beliefs and perceptions of a common set of investors outside of the country itself, is a matter of interpretation.

Additional robustness checks

The Appendix contains a number of additional robustness checks. Beyond including and excluding sets of firms from different aggregations of country risk, we also consider weighting and stratifying the sample by firm size. In Appendix Table 12, we find that variations of our measure that over-weight larger firms, for example by excluding small firms (and thus, in particular, small American firms that are over-represented in our sample), explain the patterns of capital flows slightly better than our baseline (unweighted measures). However, these apparent gains in precision are small and not statistically significant.

Expanding on this theme, Appendix Table 13 replicates our findings in Table 8 using only the perceptions of non-U.S. firms. Although U.S. firms make up almost half of our sample of earnings calls, dropping them from the analysis makes little difference to our findings.

5. CONCLUSION

Understanding the international propagation of risks and crises is essential for policymakers concerned with sudden stops, contagion, the stability of the international financial system, and the cross-border impacts of monetary and fiscal policies. A major obstacle to studying these phenomena, however, is a lack of measurement: aggregate measures of country risk are often silent as to whose perceptions of a given risk are changing, why they are changing, and how these same risks affect firms and decision makers in other countries.

In this paper, we argue that a granular measurement of the risks and opportunities that managers and investors at each of thousands of listed firms around the world associate with a given foreign country at a point in time is a key step in making progress on these questions. By flexibly aggregating our firm-country-quarter-based measures we are able to disentangle local from global crises, name the sources that managers attribute these crises to, and characterize in detail the transmission of these risks to firms around the world.

We use our new measures to deliver four main insights: First, almost all large spikes of risk in our sample had a clearly attributable source, which includes political crises, natural disasters, sovereign default, trade disputes, and other economic worries. Second, while the transmission of risk across borders typically follows a gravity structure, it often changes significantly during crises. Third, elevated perceptions of a country's riskiness are associated with significant falls in local asset prices, capital outflows, and a higher likelihood of sudden stops. Fourth, the risk perceptions of financial firms appear particularly useful for explaining variation in the most volatile components of capital flows.

Beyond the immediate applications explored in this paper, we believe our methodology opens the door to a range of future research questions. The underlying microdata and all of our aggregate time series are posted at country-risk.net, allowing researchers to explore a range of questions on global risk perceptions and their consequences.

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Data Availability Statement

Unless indicated otherwise, the data and code underlying this research are available in our replication package on Zenodo https://doi.org/10.5281/zenodo.7783429.

The main data source of this paper are the transcribed earnings calls from Refinitiv (2021). This is a commercial data set that can be subscribed through various products of Refinitiv, including Eikon, Workspace, or a dedicated API. We last updated our earnings call data in January 2021.

We also make use of other commercial and non-commercial data sets. For a complete Data Availability Statement, please refer to Online Appendix A or the `readme.md` file in the aforementioned replication package.

Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

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