Sources and Transmission of Country Risk*

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Abstract

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 associate with each foreign country at each point in time. Flexibly aggregating this firm-country-quarter-level data allows us to measure the evolution of risk perceptions associated with each country, identify the sources of this risk, and characterize its transmission between each origin and each destination. We demonstrate that elevated perceptions of a country's riskiness are associated with significant falls in local asset prices, capital outflows, and reductions in firm-level investment and employment. We also provide direct evidence of a novel type of contagion, where risk transmitted from foreign countries affects the investment decisions and valuations of domestic firms. While the aggregate transmission of risk between countries largely follows a gravity structure, this pattern can change dramatically during crises. For example, while sovereign debt crises tend to propagate predominantly to financial firms in traditionally exposed countries, risks relating to the Global Financial Crisis and the Fukushima nuclear disaster propagated globally and in a highly irregular fashion. Finally, we use our measures to provide direct evidence that heterogeneous currency loadings on perceived global risk help explain the cross-country pattern of interest rates and currency risk premia.

Keywords: country risk, contagion, investment, employment, textual analysis, earnings calls

JEL codes: D21, F23, F30, G15

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1. Introduction

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 their products, sell their products, or be otherwise exposed as holding up 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 measure country risk and quantify its transmission across borders. We measure perceived country risk at the firm-country-quarter level by measuring the share of time that global firms' executives and investors spend discussing commercial risks related to countries around the world. In particular, we apply natural language processing (NLP) to more than 300,000 English-language conference call transcripts of publicly listed firms headquartered in 82 countries to measure the perceived risks and opportunities each firm associates with each of 45 major economies that collectively cover more than 90% of world GDP.

The primitive of our analysis and our key contribution is to measure how much commercial risk firm i headquartered in country $d(i)$ associates with country c in quarter t. That is, we take a highly granular approach to measuring country risk that allows for flexible aggregations: for example, with a suitable aggregation we can separate global risks from those associated with particular countries, firms, and industries; separate the perceptions of different types of firms such as foreign vs. domestic 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 text. This allows us to distinguish variation in perceived risk (the second moment) from variation in perceived opportunities (the first moment), and understand the sources of risks and opportunities that firms face.

After validating our granular measure, we successively aggregate it into four different dimensions, analyze each in turn, and illustrate how these aggregations relate to one another. 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 45 countries.[1] We use these time series to systematically identify local and global spikes in risk ("crises") over the last two decades. For each crisis episode, we then 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 sources of variation in Country Risk without much guesswork.

Using these aggregate time series of Country Risk, we then turn to examining the effects of fluctuations in aggregate Country Risk, demonstrating that increases in a country's perceived riskiness are accompanied by sharp declines in equity prices, increases in equity volatility, a depreciated exchange rate, and increases in sovereign credit default swap (CDS) spreads. We then document a similar relationship between risk and global capital flows. In particular, we find that elevated levels of Country Risk coincide with foreign investors pulling capital out of the country; this result holds even conditional on country and year-quarter fixed effects, indicating that these flows are moving with country-specific fluctuations in riskiness.[2]

Consistent with its significant effect on asset prices and capital flows, we also find that elevated Country Risk is associated with reductions in firm-level investment and employment of firms based in the country. Importantly, these results hold even conditional on the firm's own perceived risk as well as on firm and year fixed effects. We view these results as providing strong evidence that fluctuations in Country Risk are an important determinant of real allocations, above and beyond its associations with asset prices and capital flows.

We then create aggregate measures of Country Risk as perceived by different subsets of firms. That is, we obtain multiple aggregate measures of risk for the same country that allow us to distinguish the perceptions of foreign vs. domestic firms, those of financial vs. non-financial firms, and those of financial firms from those in the same sector as the firm in question. We find that it is the perception of foreign firms rather than domestic firms

[1] Thus we use "Country Risk" to mean the perceived commercial 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)).

[2] There is a large literature, beginning with Calvo et al. (1996) demonstrating the importance of global "push factors" in explaining global capital flows. These push factors speak to the relative importance of common shocks, particularly for developing countries, in explaining global capital flows. Our analysis introduces a new force: we demonstrate the importance of a country-specific factor (Country Risk) in explaining capital flows.

that best accounts for the patterns of capital inflows and sovereign credit spreads; and that portfolio flows, a volatile component of capital flows of particular focus from policymakers, is best explained by the perception of Country Risk of financial firms. Similarly, firm-level investment and employment loads more on country risk-perceptions of financial firms than firms in the same sector.

Having demonstrated the importance of aggregate Country Risk, we then in the second step turn to studying the propagation of foreign risks at the firm-level. For each firm i in quarter t we sum our measures of risk across all foreign countries c. This yields a measure of how much foreign risk each firm is exposed to in each quarter, which we refer to as "Foreign Risk." We find that firm-level exposure to foreign risks is quantitatively important: About 20% of the overall variation firm-level risks is accounted for by foreign sources. We then demonstrate that when a firm's Foreign Risk increases, it reduces its investment and employment. This occurs above and beyond not just fluctuations in Country Risk of the firm's own home country, but also the firm's other (not foreign-related) risks. Notably, we show evidence that this kind of spillover of Foreign Risk to real outcomes often operates through complicated exposures that are not always well-approximated by customer-supplier relationships or the firm's observable foreign investments. These results thus provide clear evidence that contagion (the spillover of foreign country risk on firm-level outcomes) is an important driver of firm-level outcomes.

These firm-level effects of Foreign Risk motivate us to study in a third step the transmission of risk across countries more systematically. 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 associate with country c at time t (that is, we average across all i in d). We refer to this measure as Transmission Risk and use it to show that, during normal times, the transmission of risk across countries follows a gravity structure: Firms on average worry more about risks originating in countries geographically closer to them, that speak the same language, and that were in a colonial relationship.

However, despite this regular pattern of transmission of risk during normal times, we also find that these patterns can shift dramatically during periods of crisis. To systematically quantify these shifts, we calculate the pattern of transmission for each of the 33 major 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 intercept, slope estimates, and R^2 from these regressions can serve as useful characterization of how a crisis associated with a particular origin country affects the perceived commercial risk of firms based in other countries. For example, our analysis shows that the beginning of the Global Financial Crisis (GFC) in the United States in 2008 and the beginning of the Coronavirus pandemic in China in the first quarter of 2020 are the two crises with the relatively largest degree of global transmission in our sample: They transmit risk to firms in virtually all parts of the world. By contrast, the Thai Flooding of 2011 or the Egyptian Revolution of 2011 came with strong bilateral transmission of risk: Firms in countries traditionally exposed to the two countries increase their risk perceptions disproportionately, but with a relatively limited impacts on the perceived riskiness 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. For example we find that the Fukushima nuclear disaster engendered the crisis with the most irregular transmission pattern in our sample: We observe a strong transmission to faraway 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 primarily through financial or non-financial firms. We document a large degree of heterogeneity across crises; for example, financial firms experience nearly double the increase in perceived risk as non-financial corporates from the Italian sovereign debt crisis but only half the increase as non-financial firms from the US-China Trade War.

Across the 33 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 natural disasters and episodes of political instability. Similarly, crises originating in emerging markets and sovereign debt crises tend to have relatively stronger bilateral transmission.

Finally, we aggregate Country Risk to a single time series of what we refer to as Global Risk in order to explore the connection between Global Risk and exchange rates (Lustig et al., 2011). We demonstrate that heterogeneous loadings on our text-based measure of Global Risk explain a large fraction of the cross-sectional variation in exchange rate movements and currency returns. Most notably, we provide direct evidence that the US dollar, the euro, and the Japanese yen systematically appreciate when Global Risk perceptions spike. These results provide strong evidence for a prominent theoretical literature, where our new measures of perceived risk allow us to examine these theories more directly than was previously possible.

Related Literature This paper contributes to four strands of the literature. First, we contribute to the literature on international asset pricing and global risk. Colacito and Croce (2011) demonstrate that common long-run risk across countries can explain a number of international finance puzzles. Colacito et al. (2018) characterize how common risk to long-run growth news can reconcile the patterns of international capital flows with the data. Gourio et al. (2013) theoretically examine the implication for asset prices and exchange rates if countries have heterogeneous loadings on global risk. Gourio et al. (2015) examine how fluctuations in political risk can rationalize patterns in international capital flows. Bekaert et al. (2013) demonstrates that looser monetary policy reduces risk aversion and uncertainty. Rey (2015) and Miranda-Agrippino and Rey (2020) demonstrate how fluctuations in global risk generate common movement in asset prices and macroeconomic activity around the globe. Relative to the existing literature, we are able to precisely define and measure risk associated with a given country and use our micro-based measure to reexamine some of these classic questions.

The second branch of the literature studies the determinants of global capital flows and sudden stops. Calvo et al. (1996) demonstrated the importance of shocks emanating from global financial centers for fluctuations in capital flows to emerging markets, emphasizing the importance of "push factors" in the determination of global capital flows. 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 of country risk to demonstrate the importance of the perceptions of country-specific risk in driving global capital flows, with these perceptions predominantly coming from firms and investors based in large developed countries. We therefore bridge the gap between these 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.[3]

Third, a large empirical and theoretical literature studies the effects of micro and macro uncertainty on asset prices investment, employment growth, lobbying, and the business cycle within the United States and other countries (Bloom et al., 2007; Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015; Handley and Limao, 2015; Giglio et al., 2016; Koijen et al., 2016; Kelly et al., 2016; Mueller et al., 2017; Bloom et al., 2018; Besley and Mueller, 2018; Hassan et al., 2019; Bekaert et al., 2019), Pflueger et al. (2020). We add to this literature by showing that fluctuations in country risk account for substantial variation in international capital flows and asset prices across countries, and by tracing transmission of country risk across borders to granular exposures at the firm-level. In addition, our findings are consistent with a prominent narrative in the policy-oriented literature that foreigners' perceptions of country risk directly affect local outcomes, particularly in emerging markets.

Fourth, we contribute to the growing literature that applies natural language processing in macroeconomics and related fields. In particular, we contribute to the subset of this literature that generates measures of risk from text, for example, Baker et al. (2016) use newspapers to measure economic policy uncertainty by counting the daily number of newspaper articles featuring the words 'economic,' 'policy,' and 'uncertainty.' Hassan et al. (2019) use the transcripts of earnings conference calls to measure firm-level political and non-political risk in the United States, 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. Calomiris and Mamaysky (2019) explore the connection between text-based measures from news articles and stock returns around the world. We differ from these existing approaches in three respects. First, basing our measures on hundreds of thousands of firm-quarter-level documents allows us to flexibly decompose perceptions of domestic and foreign agents, and those of sub-groups of decision

[3]Bekaert et al. (2014a) examine the role of political risk, estimated from sovereign spreads, drives the pattern of foreign direct investment. Kalemli-Özcan (2019) explores the differential transmission of risk movements for emerging and advanced economies.

makers, for example those at financial and non-financial firms. Second, these decompositions then enable us to understand directly from the underlying text what events drive a given peak in risk, and to document the transmission of country risk across borders, by measuring this transmission directly at the firm-level. Third, using conditional rather than unconditional word-counts we are able to separate the role of risk (the second moment) from that of positive and negative shocks (the first moment).

Finally, we contribute to the literature on contagion and the international propagation of shocks. Forbes (2012) surveys this large literature, highlighting the challenge in a common definition of contagion. Forbes and Rigobon (2002) examine whether higher stock market correlations during crises represents contagion or high levels of interdependence. Bekaert et al. (2014b) examines equity market contagion during the global financial crisis. Huo et al. (2019) and Baqaee and Farhi (2019) explore the importance of country-specific shocks and the transmission of common shocks around the world. We introduce a new measure of the transmission of global risk by precisely measuring how much global decision makers talk about specific countries, and asking whether firms discussing foreign countries see their investment and employment respond more to fluctuations in perceptions of the riskiness of the country in question. By beginning with firm-level variation, we are able to explore the transmission of global risk at varying degrees of disaggregation. For instance, we are able to examine which types of country risk are more likely to affect financial firms and which are more likely to be transmitted to the non-financial corporate sector.

The structure of the paper is as follows. Section 2 formalizes how we move from measurements of country risk at the micro level to macro aggregates. Section 3 introduces the data and the introduces the methodology for measuring country risk a the firm level. Section 4 aggregates the firm level measures to the macro level, validates the new measures, introduces a number of new stylized facts about the nature of country risk, and explores the explanatory power of our aggregate measure country risk for aggregate financial and macroeconomic patterns. Section 5 studies the firm-level effects of Country Risk and Foreign Risk. Section 6 examines the transmission of risk at the firm and country level. Section 7 explores the connection between risk and exchange rate movements. Section 8 concludes.

2. Conceptual Framework

The starting point of our analysis is a measure of the risk that firm i headquartered in country $d(i)$ associates with country c during quarter t

$$CountryRisk_{i,c,t}. \tag{1}$$

Our goal is to use this micro, firm-based, measure of country risk to achieve three core objectives: (i) aggregate to macroeconomic measures of country risk as perceived by different sets of firms and investors ("Country Risk"); (ii) assess how much overall foreign risks a given firm perceives at a given point in time ("Foreign Risk"), (iii) examine the global transmission of risk from each origin to each destination ("Transmission Risk"), and (iv) create a measure of global risk as perceived by firms around the world ("Global Risk").

Our aggregations of the firm-level measure of country risk take the form

$$CountryRisk^{K}_{c,t} = \frac{1}{N_K}\sum_{i\in K} CountryRisk_{i,c,t} \tag{2}$$

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 commercial risk emanating from country c at time t for the set of firms K. We refer to this measure as Country Risk. The power in 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 groups 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 consider different subsets of firms. This allows us to examine whether their risk perceptions differ and, if they do, whose perceptions are the relevant drivers of macroeconomic and financial aggregates, as well as of firm-level investment and employment decisions. For instance, in our analysis below we consider separately the perceptions of foreign firms (*NHQ*), financial firms (*FIN*), American firms (*US*), and firms only in a particular industry.

In addition, because our aggregate measure, $CountryRisk^{ALL}_{c,t}$, begins with firm-level data, we are able to perform two sets of exercises to uncover the sources of Country Risk. First, we can explore which types of firms drive specific fluctuations in aggregate country risk; for example, we can isolate episodes of particular concern for financial firms. Second, utilizing our text-based approach for the actual measurement of $CountryRisk_{i,c,t}$, we can directly understand what concerns firm i has about country c at time t that is driving the movements in their risk perceptions. We will explore the implications of these aggregate risk measures for financial and real outcomes in Section 4.

The second strand of our analysis explores the amount of foreign risk facing a particular firm. At the firm-quarter level, we define

$$ForeignRisk_{i,t} = \sum_{c \neq d(i)} CountryRisk_{i,c,t}. \tag{3}$$

$ForeignRisk_{i,t}$ for firm i at time t is the sum of the risk the firm associates with all countries around the world, excluding its home country.[4] We refer to this micro-level measure as Foreign Risk and use it to assess the firm-level spillovers of Foreign Risk across borders, and to disentangle the effects of risk perceived by foreign and domestic firms on firm-level outcomes.

Third, we then use the same approach to measure the aggregate transmission of risk from each origin country to each destination country at each point in time:

$$TransmissionRisk_{o \to d,t} = \frac{1}{N_d} \sum_{i \in d} CountryRisk_{i,o,t} \tag{4}$$

This measure is calculated by summing over the risk that all firms based in country d perceive in country o at time t. In this sense, it captures how much risk is transmitted from country o to country d. We refer to this measure as Transmission Risk.

To capture the general pattern of the transmission of risk across countries, we can average Transmission Risk over time to calculate

$$\overline{TransmissionRisk}_{o \to d} = \frac{1}{T} \sum_{t} TransmissionRisk_{o \to d,t} \tag{5}$$

This bilateral, time-invariant transmission across countries shows the average pattern of transmission of risk across country pairs and can therefore be used as a benchmark for

[4] $DomesticRisk_{i,t}$, or the risk the firm associates with its home country, would simply be $CountryRisk_{i,c(i),t}$, where $c(i)$ denotes the home country c of firm i.

examining whether the pattern of the transmission of risk during a given crisis is different than other periods.

Finally, we aggregate our measure across all firms and destinations to create a text-based measure of global risk,

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

which is simply the average of $CountryRisk_{i,c,t}$ over firms and countries. We refer to this measure as Global Risk.

While the literature has many proxies for global risk, such as the VIX (Kalemli-Özcan (2019), Di Giovanni et al. (2017)) or the Global Factor of Rey (2015) and Miranda-Agrippino and Rey (2020), the overwhelming share are based on asset prices. This measure, by contrast, aims to directly measure how much executives and investors at global firms worry about risks emanating from foreign countries.

Finally, while the focus of the paper is on Country Risk, we conduct analogous measurement and aggregation exercises using the sentiment firm i has towards country c at time t ($CountrySentiment_{i,c,t}$). We regularly use these sentiment measures as a control for variation in the first moment, that is, as a control for whether there is good or bad news emanating from a given country at a given point in time.

3. 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. We begin with a description of the data and then turn to the methodology.

3.1. Conference Call Transcripts

The core of our dataset is the complete set of 306,589 English-language earnings conference call transcripts from Refinitiv EIKON from 2002-2020. These conference calls cover 11,865 firms that are headquartered in 82 countries. Generally, firms will have four calls per years, 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, the calls last around 45 minutes. In order to prepare the earnings call transcripts for analysis, we first remove all metadata such as title, date, speaker names with the goal of keeping only spoken text from the earnings call transcripts. We also remove all non-alphabetic characters, but do not force words to be lower case in order to facilitate the subsequent country name matching (e.g. to distinguish Turkey from the animal turkey).

Appendix Table 1 summarizes our country coverage. Of the 11,831 firms, 6,457 are headquartered in the United States. The next three countries with the highest coverage are Canada, the United Kingdom, and Australia with 885, 528, and 401 firms, respectively. This ordering reflects our focus on English-language transcripts and, of course, firms headquartered in English-speaking countries are more likely to conduct their conference calls in English. Nevertheless, as seen in the table, there are 28 countries for which we cover at least 40 firms in sample, reflecting a wide range of coverage of our dataset. In addition, Appendix Figure 1 shows that it is the largest firms are disproportionately likely to appear in our dataset and shows that even relatively small American firms are likely to be included. In this sense, one can best think of our measure as capturing the concerns of multinational firms and global investors.

3.2. Country-Specific Training Libraries

A key step in measuring country risk is to identify when the conference calls are focusing 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. The service covers 56 countries' rules in critical areas such as setting up a business, human resources, incentives, taxes, and intellectual property. It will allow you to get to grips with all key regulations and also to assess how ongoing regulatory changes will affect your organisation."[5] The reports offer 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

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

to reliably compare across country reports. 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 56 countries for which Country Commerce Reports exist, we restrict our analysis to the largest 45 economies, collectively covering 90.6% of world GDP in 2014.[6] For each of these 45 countries, we obtain all reports for 2002-2019, remove non-alphabetic characters, and collect the remaining text in a single training library.

We use the Country Commerce Reports to identify a training library for each country c. A country-specific training library is simply a set of word combinations that consist of two components: The first component is the set of all pairs of adjacent words (bigrams) that occur in a country's Country Commerce Report, after removing bigrams that are likely to be used in conversational language.[7] The second component is the intersection of single words (unigrams) in a country's Country Commerce Report and of unigrams in a separate country-specific names library that contains country, region, and city names.[8] This is to allow for the fact that countries and places are often described by single words, which means that a bigram-based training library is unlikely to contain all relevant combinations of these unigrams with other words. In what follows we will refer to a word combination from a training library, which in our case can be a unigram or a bigram, simply as "bigram."

We then assign to each bigram a weight that indicates how strongly it is associated with discussions about 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]

[6] We exclude Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Kenya, Nicaragua, Panama, Peru, Uruguay, and Vietnam

[7] To this end, we use all bigrams from the University of Santa Barbara Corpus of Spoken American English Du 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] Our country names library consists of the union of unigrams from the following: All adjectival and demonymic forms of the country name from Wikipedia and the CIA World Factbook; the names of towns with more than 15,000 inhabitants in 2018 and the administrative subdivisions in the country, both from geonames.org.

[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 analyze the underlying text.

The first is the bigram's relative frequency in the training library of country c; the second is the bigram's inverse frequency across training libraries – a penalty for bigrams that also appear in the training libraries of many other countries:

$$\omega(b,c) = \frac{f_{b,T^c}}{B_{T^c}} \times \log(45/f_{b,\mathbf{c}}), \tag{6}$$

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, and $f_{b,\mathbf{c}}$ is the number of training libraries in which b occurs at least once. The first term, commonly denoted 'term frequency' (tf), thus simply 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 are used predominantly in discussions of a given country and 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 we might deem this mention less informative about whether or not a given text excerpts contains discussions of Belgium.

Finally, because country names themselves repeatedly appear as parts of lists in the Country Commerce Reports (e.g. as part of a list of bilateral withholding tax rates), they tend to get substantially downweighted. This is because their *idf* becomes small as they appear across more Country Commerce Reports. We therefore give *all* bigrams containing the country's name as a unigram a floor: It receives the maximum $tf \times idf$ of any bigram containing the country's name. 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 1 gives intuition for the workings of our algorithm by showing the top 20 bigrams by tf-idf in our training library for Greece, Turkey and Japan. While for each country the variants of country name are among the most important bigrams "Greek", "Turkish", "Japanese"), we can see how successful the Country Commerce Reports are in identifying important country-specific phrases and institutions. For instance, in Panel A for Greece, we see that the fifth most important bigram is "ND government," a short-hand referring to the "New Democracy" center-right political party.[10] Similarly, for Turkey we see that the third

[10]Note that "an AE" is similar to a US limited liability company,

most important bigram is "Gazette No" and the sixth 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 and the Japanese Patent Office, respectively. In all of these cases, these phrases or short-hand would be obvious to experts in the area, but there would be no ex ante way to say which political parties or ministries would have their names abbreviated in conversation and which would be stated in full. Our approach is able to systematically extract the expertise embedded in the Country Commerce Reports and then use them to identify the country in question far more extensively than simply waiting for a call participant to say "Greece" or "Japan."

3.3. Measuring and validating Firm-Level Country Risk and Sentiment

Measurement With our country-specific training libraries in hand, we can turn to the measurement of firm-level exposure to foreign countries and the risk and sentiment they associate with those foreign countries. Our simplest measure of country exposure counts the number of occurrences of bigrams indicative of conversation about country c, weighted by $\omega(b, c)$. This means bigrams that the training library more confidently ascribed to a given country also receive more weight. We divide this sum by the total number of bigrams in the transcript to account for differences in the length of the earnings call:

$$CountryExposure_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \omega(b, c), \tag{7}$$

where $b = 0, 1, ...B_{it}$ are the bigrams contained in the earnings call of firm i at time t.

To create our measure of Country Risk, we build on the methodology of Hassan et al. (2019) by conditioning the weighted count of bigrams indicative of conversations about country c on being in close proximity to a synonym for risk or uncertainty:[11]

$$CountryRisk_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \{1[|b-r| \leq 10] \times \omega(b,c)\}, \tag{8}$$

where r is the position of the nearest synonym of risk or uncertainty.[12]

Finally, we construct an equivalent measure of country sentiment. Instead of conditioning on bigrams appearing close to a synonym for risk, we count positive or negative tone words ("sentiment") used in conjunction with these country-specific bigrams:

$$CountrySentiment_{i,c,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left\{ \left(\sum_{g=b-10}^{b+10} S(g) \right) \times \omega(b,c) \right\}, \tag{9}$$

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 3 lists the top 100 positive and negative sentiment words.

Validation Before turning to our analysis of country risk, we validate our measures at the micro-level. In Table 2, we validate our firm-level exposure measure. In particular, we regress firm i's average exposure to country c, $CountryExposure_{i,c} = (1/T) \sum_t CountryExposure_{i,c,t}$ on other firm-level variables that should correlate with a material exposure to a country. If our text-based exposure measure is systematically behaving as it should, we would it expect it to covary 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 them to discuss that particular country more during their earnings calls. To measure this variable, we use the Geographic Segment data from Worldscope. This data is extracted from annual reports, where under GAAP and IFSR accounting rules, firms need to report all sales destinations

[11] We obtain all synonyms for risk, risky, uncertain, and uncertainty from Oxford Dictionary. Appendix Table 2 lists the top 100 risk synonyms.

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

from which they earn more than 10% of their revenue or have a “material interest.” We therefore classify the firm as having a segment data link if the country is listed in this report in 2016.[13] Third, we use a firm's subsidiaries in 2016 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 an earnings call.

The regressions in Table 2 provide strong confirmation for our measure. Firms are 2.6 standard deviations more exposed to their headquarter country than other firms, and firms with a sales link in the segment data are 1.4 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 in Orbis. 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.

4. From Micro Measurement to Aggregate Country Risk

4.1. Aggregate Country Risk and Sentiment

Having constructed firm-level measures of country risk and sentiment, we next turn to aggregating these measures to the country level. For each aggregation of $CountryRisk^{K}_{c,t}$, we implement Equation 2. The widest definition, and the one we primarily use throughout the paper, is where $k = ALL$, that is, where we include all firms that hold a conference call in quarter t.[14]

Table 3 presents summary statistics for our various measures of country risk and country sentiment, including those where we restrict K to firms that are *not* headquartered in country c, (NHQ); those were we restrict to domestic firms only, (HQ); and those where we restrict to financial firms only, (FIN). For our analysis of firm-level outcomes below, we also construct measures that condition only on firms in the same (SIC-1-digit) sector as the firm in question,

[13]However, this coarse measure will miss a lot of 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 because these sales relationship would not necessarily be disclosed.

[14]Our analysis uses the headquarter country of a firm, rather than the legal incorporation to more closely map to economic decision-making. See Coppola et al. (2020) for a detailed discussion of these issues.

($OWNIND$). 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.

Properties of Country Risk and Sentiment With our quarterly time series in hand for 45 countries across 18 years, we now turn to establishing two stylized facts about the nature of Country Risk and Sentiment. We begin by characterizing the mean of Country Risk and Sentiment across countries. Recent work, such as Rey (2015) and Miranda-Agrippino and Rey (2020) has emphasized the co-movement of global risk across countries, where "risk" generally is measured as the common component of asset price movements.

First, we directly measure the extent to which Country Risk covaries across countries. In particular, the first principal component of Country Risk explains 65.4% of country level variation. Similarly we find that that the first principal component of Country Sentiment explains 89% of the variation in Country Sentiment. We therefore provide strong evidence in favor of the arguments on the importance of common fluctuations in Country Risk. We return to this issue in Section 7, where we show direct evidence that these global co-movements give rise to a strong factor structure in exchange rates.

Second, we find that the mean within-country correlation between $CountryRisk_{c,t}$ and $CountrySentiment_{c,t}$ is -0.28. As argued by Berger et al. (2020), we can thus confirm that the first moment (Country Sentiment) and second moment (Country Risk) are correlated, where higher risk is often associated with lower sentiment (that is, bad news). 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.[15]

Nevertheless, the two series are not mirror images of each other, and they often diverge for economically important reasons. For instance, in Appendix Figure 2, 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

[15] 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.

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. As we will show econometrically below, this example holds true more generally, where both measures have meaningful independent variation.

4.2. Country Risk and Crises

We now use our Country Risk measures to examine the recent history of each of the 45 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. While the 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 introduce our fourth measure, Global Risk, which is calculated as the mean of Country Risk across our 45 countries. Figure 1 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 Global Financial Crisis (GFC) and the recent global pandemic. In addition, the Great Moderation (i.e Bernanke (2004), Galí and Gambetti (2009)) is visible in the time series, with Global Risk from 2002-2006 lower than the entire period since the GFC. Finally, the graph also shows another spike during the European sovereign debt crisis around 2011. Figure 1 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.

We next turn to identifying country-specific crises. Using our aforementioned threshold of two standard deviations, we consider a country to be in a crisis when its perceived level of Country Risk is at least two standard deviations above the sample 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 consider it a local crisis and mark it with a gray dot in the country's graph. For each of these episodes we then read all high-impact snippets of text of the top 30 firms that associate the highest risk with the country, and label the episode to summarize firms' predominant concerns at the time.

In Figure 2, we plot the aggregate time series of Country Risk of the twenty countries that have a local crisis according to our definition, with the ordering reflecting the number of local crises. Appendix Figure 3 reports the equivalent graphs for all countries without a local crisis.[16] In addition to identifying crises at the country level, we use a firm level regression to systematically classify each local crisis into whether they are disproportionately driven by concerns among financial firms or not. If we find such a disproportionate rise among financials we mark the local crisis with a hollow red circle, while all other local crises are marked with a solid red bullet.[17] The details of this financial classification will be discussed more in Section 6.

The figure shows a number of notable features. First, the time series for most countries show clearly the impact of the two global crises in our sample, although there is also substantial idiosyncratic variation. Second, for all but two of these thirty-six 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 center on the risk of lower growth and financial volatility. These are followed in 2018-2019 by uncertainty about trade policy and the escalating US-China trade war. The final one, 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 local crisis surrounding Latin American crisis of 2002 and the subsequent election of Lula da Silva, as well as a long-period of upheaval surrounding the corruption scandals and recession of 2015-2016. Great Britain records consecutive

[16] We also consider countries as having no local crises if its only crises are following a global crisis as defined before: being above two standard deviations in Figure 1.

[17] For a given crisis, we regress demeaned firm level Country Risk on an indicator of whether the firm is a financial firm, defined as having its SIC code between 6000 and 6800. If the coefficient on the dummy variable is positive and statistically significant, we say that the local crisis is disproportionately driven by financials.

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 2014-15, and the concurrent sanctions and devaluation of the ruble. The United States record the onset of the Global Financial Crisis in 2008, which again later becomes a global crisis; the Deepwater Horizon oil spill; and another spike in uncertainty around the S&P downgrade of the Federal credit rating and fiscal uncertainty surrounding the debt ceiling crisis. In Thailand, the flood of 2011-12 features prominently, followed by the coup of 2014. 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.

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 from to mortgages issued in Swiss francs, 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 commercial 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, an attempt by the Venezuelan opposition to oust Hugo Chavez. The second is the failed Iranian Green Revolution of 2012.[18] These examples also highlight an important feature of our approach: because we rely on discussions of investors and executives 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 become.

[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 2.

4.3. Understanding the Variation in Country Risk

Having documented the pattern of crises across countries, we now use subsets of the aggregate series along with the micro-data to validate the patterns and zoom in on their sources.

Figure 3 shows the time series of Greek Country Risk. The gray shaded area 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. Below the graph, we show key text snippets that have received a high weight in earnings calls of firms that showed a high risk they associate with Greece during each of these episodes.[19] In Figure 2 we made systematic use of these high-impact snippets of text to identify the macroeconomic or political events listed in the figure that contribute to each large spike in perceived Country Risk. Here in Figure 3, we also show example snippets and note that these snippets indeed highlight key events of the European debt crisis, beginning with the initial realization in the second quarter of 2010 that Greece had misreported its debts and that foreign banks are 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 with Syriza's referendum and the possibility of a Greek Exit from the European Monetary Union. Consistent with the financial 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 4, 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, and the military coup in the third quarter of 2014. Interestingly, comparing the gray 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. When we turn to the high-impact snippets reported below the table, we again see that the firms are actually discussing and concerned about the events in question.

As our third example, we examine the United States in Figure 5. The US occupies a unique position in our dataset as it is not only the economically largest country, but it

[19] We select these snippets from the top 30 snippets with the highest weight after pooling and sorting all snippets from the top 100 firms with the highest level of $CountryRisk_{i,c,t}$ for country c in quarter t.

is unique in that approximately half of the firms are based in the US and the remaining half are non-US. Therefore, for the US, it is particularly informative to compare aggregate Country Risk, $CountryRisk^{ALL}_{c,t}$ with American Country Risk as perceived by American firms, $CountryRisk^{HQ}_{c,t}$, and with American Country Risk as perceived by foreign firms, $CountryRisk^{NHQ}_{c,t}$. Again using our systematic reading of high-impact text snippets, the figure labels a number of additional spikes in US risk that fall below our "crisis" threshold established above, but are nevertheless instructive. Most notably we see firms discussing risks associated with the Iraq War, the Deepwater Horizon oil spill, the fiscal cliff negotiations in late 2011, and the election of Donald Trump in 2016. While for most of these episodes foreign and domestic perceptions of US 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, see a dramatic increase in foreigners' perceptions of US Country Risk, with the increase coming from American firms far more muted. By contrast, the concern around the Fiscal Cliff in 2012 was far more concentrated in American firms. We make more systematic use of this kind of systematic divergence in risk perceptions by different kind of firms in our econometric analysis below.

4.4. *The Aggregate Effects of Country Risk*

Having examined and validated our aggregate measures, we now explore the relationship between Country Risk, asset prices, capital flows, and sovereign default risk. We begin by confirming that our measures co-move as expected with stock prices. In Table 4, we demonstrate that when Country Risk increases and Country Sentiment decreases stock returns fall. In particular, in column 2, a one percent increase in Country Risk is associated with a 0.285 (s.e.=0.041) percentage point drop in the country's (MSCI) stock return index, while a one percent increase in Country Sentiment is associated with a 0.190 (s.e.=0.034) percentage point increase in stock returns. Similarly in line with expectations, column 4 shows that changes in realized volatility of these same indices is not significantly associated with changes in Country Sentiment (the first moment), but instead loads only on variation in Country Risk (the second moment). A one percent increase in Country Risk is associated with a 0.110 (s.e.=0.022) percentage point increase in realized volatility. In sum, countries' stock prices drop and become more volatile when they are perceived to become riskier.

Having shown that Country Risk behaves in the expected way with stock returns and realized volatility, we turn to exploring its relationship with capital flows. In Panel A of Table 6, we examine country risk as a driver of global capital flows. A large literature, beginning with 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 with little of the variation explained by local factors.[20]

Using our global and country-specific measures of Country Risk, we are able to revisit this result. In column 1, we run a univariate regression of total capital inflows to a country scaled by the stock of foreign investment[21] on Global Risk (conditional on country fixed effects), and observe that inflows drop significantly when Global Risk is elevated. We view this as consistent with the importance of push factors, or the fickleness of capital flows discussed in Caballero and Simsek (2020). In column 2, we include Country Risk – a local pull factor. The coefficient on Global Risk turns statistically insignificant, while the coefficient on Country Risk is negative and statistically significant, demonstrating the importance of country specific variation in risk: A one standard deviation increase in a country's risk is associated with 0.8 percentage point drop in inflows – corresponding to a 47% 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 quarter fixed effects and see that the effect of Country Risk on capital inflows is essentially unchanged, even when we partial out all possible global variation in push factors. In column 5, we also add 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 (0.757, s.e.=0.234). The coefficient on Country Risk is reduced by

[20] While we focus on exploring the relative explanatory power of different aggregations, one could instead imagine using the micro data to ask what combination of firm-level expectations best explores or predicts a variable of interest.

[21] 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.

about half but remains strongly negative and statistically significant at the 5% level (-0.351, s.e.=0.170).

Panel B repeats this analysis, but now relates changes in the country's credit default swap (CDS) spread to *changes* in log Country Risk. The pattern is largely similar: increases in Country Risk are significantly associated with increases in the CDS spread, even after changes in Global Risk, changes in GDP growth and changes in Country Sentiment are accounted for. The coefficient in column 5 suggests that a doubling (100% increase) in country risk is on average associated with a 2.281 (s.e.=0.821) percentage point increase in the country's CDS spread.

In Table 6, we unpack our aggregate Country Risk series to better understand the sources of its explanatory power. In Panel A, we continue our examination of capital inflows. The first column examines aggregate Country Risk, $CountryRisk_{c,t}^{ALL}$. Next, we look at the effect of Country Risk as perceived by all firms headquartered in the United States, $CountryRisk_{c,t}^{US\ firms}$. We find that the point estimate increases but is now slightly less precisely estimated. The coefficient goes down by about a third when in column 3 we instead look at the effect of Country Risk as perceived by foreign firms, $CountryRisk^{NHQ}$. Column 4 continues focusing on foreign firms but now introduce a new control: the average across all firms headquartered in c of the risk they face. We denote this variable by $\overline{FirmRisk_{i,t}}_{c,t} := (1/N)\sum_{i \in c(i)} FirmRisk_{i,t}$, 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 captures the total risk as perceived by firms based in the country, regardless of where this risk is coming from. Remarkably, adding this control barely attenuates the coefficient on $CountryRisk^{NHQ}$, with $\overline{FirmRisk_{i,t}}_{c,t}$ also statistically significant and the R^2 increasing. 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 column 5 of panel A, we instead control for Country Risk as perceived by the firms based in that particular country, by averaging $CountryRisk_{i,c,t}$ for all i with their headquarters in c. This variable is insignificant, demonstrating that, on average, the explanatory power for capital flows is coming from foreign rather than domestic risk perceptions. While it is entirely conceivable that this pattern arises because perceptions of domestic agents ($CountryRisk^{HQ}$

and $\overline{FirmRisk_{i,t}}_{c,t}$) are measured with more error than foreigners' perceptions of a country's riskiness ($CountryRisk^{NHQ}$), it also suggests that foreigners' perceptions may be an important variable in and of itself. That is, our results are 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 and of themselves.

Column 6 of panel A contrasts the information content of our measure of Country Risk with another text-based measure, the World Uncertainty Index (WUI) compiled by Ahir et al. (2018). Rather than operating on firm-level texts, this alternative measure counts the frequency of synonyms of risk and uncertainty directly in the Economist Intelligence Unit country reports. While this alternative measure is positively correlated with ours (the within-country correlation is 0.19), controlling for it in the regression changes the coefficient on $CountryRisk_{c,t}^{NHQ}$ only slightly.[22]

In column 6, we consider the relative explanatory power of the risk perceptions of financial (FIN) and non-financial (NFC) firms. We find that both are strongly predictive of aggregate capital inflows. However, in column 7, we look at the drivers of one component of capital flows: portfolio inflows. These purchases of stocks and bonds are sometimes referred to as "hot money" as they are notoriously flighty. In this case, we see that it is the risk perceptions of financial firms that explains movements in this component of capital flows.

In Panel B of Table 6, we run the same set of regressions but with sovereign CDS spreads as the dependent variable. Once again, we find that the bulk of the explanatory power comes from firms based outside the country. This again speaks to the idea that both global capital flows and asset prices may partly be driven by perceptions of decision makers based outside

[22] Appendix Table 4 expands on this theme, comparing and contrasting the information content of $CountryRisk^{ALL}$ with that of both WUI and country-level indices of Economic Policy Uncertainty (EPU) (Baker et al., 2016), which are available for 22 countries. The within-country correlation between these 22 EPU measures and $CountryRisk^{ALL}$ is 0.41. Across specifications, we find that these alternative text-based measures also tend to correlate with capital inflows, CDS spreads, as well as the firm-level outcomes we discuss in detail below, with the the predicted sign. However, the table also shows that $CountryRisk_{c,t}^{ALL}$ is more strongly associated with all of these aggregate and firm-level outcomes and dominates when the alternative measures are controlled for. 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 of 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 $\overline{FirmRisk_{i,t}}_{c,t}$ than $CountryRisk_{c,t}^{ALL}$.

the country in question.

Putting all this 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. Therefore, we do find that it is the country specific risk as perceived by foreigners that drives global capital flows, but 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.

4.4.1. Alternative Weighting

Up to this point, we have treated the perceptions of all firms as equally important in driving country risks. Yet, one might wonder whether the perceptions of some firms are more relevant for aggregate activity than others. To explore this possibility, we introduce a weighted version of our measure:

$$WeightedCountryRisk_{c,t}^{K} = \frac{1}{N_{K,t}} \frac{1}{\sum_{i \in K} \eta_{i,t}} \sum_{i \in K} \eta_{i,t} CountryRisk_{i,c,t}$$

where $\eta_{i,t}$ is the firm's weight at time t. We consider here weighting schemes based on firm size measured using firm assets. In Appendix Table 8, we consider weights as the raw dollar value of assets, the log of a firm's assets, a Box-Cox transformation of assets, and separate indices for small and large firms. As we show in the table, all weighting schemes except for the dollar value of assets are very similar to our baseline unweighted case. The version with asset weights is far more volatile because of the skewed nature of the firm-size distribution. As measurement error will always be larger at the firm-level than at the country level, weighting based on a skewed distribution will effectively behave as if we have very few observations. This lead us to prefer the unweighted version. In Appendix Table 8, we find that using log of assets as the firm weight when creating the country level measure actually explains the pattern of capital flows slightly better than the unweighted version.

5. The Firm-level Effects of Country and Foreign Risk

5.1. The Real Effects of Country Risk

Having demonstrated the robust relationship between Country Risk and the financial side of the economy, we now turn to examining its connection to the real side of the economy. In particular, we ask the question of whether increases in Country Risk coincide with declines in firm-level investment and employment. Importantly, we want to see whether Country Risk can account for firm level investment and employment decisions above and beyond the firm's perception of its own risk, $FirmRisk_{i,t}$. In columns 1 and 2 of Table 7, we run regressions of the form

$$y_{i,t} = \delta_i + \delta_t + \delta_c + \beta\, CountryRisk^{NHQ}_{c(i),t} + \gamma FirmRisk_{i,t} + X'\zeta + FE_{i,t} + \epsilon_{i,t} \tag{10}$$

where $y_{i,t}$ is either the log of firm i's investment rate at time t or the change in firm i's total employment between t and $t-1$, and δ_i, δ_c and δ_t stand for firm, country, and time fixed effects, respectively. We consider investment in Panel A and employment in Panel B of Table 7.

Column 1 includes firm and year fixed effects. We see $CountryRisk^{NHQ}$ enters negatively and strongly significantly, meaning that increases in the risk perceptions of foreigners of a firm's headquarter country is associated with falls in investment and employment. In Column 2, we split Country Risk into two components: the perceptions of financial firms (*FIN*) and the perceptions of other companies in the firm's own industry (*OWNIND*), excluding financial firms. For both investment and employment, we find that the explanatory power comes almost entirely from the perceptions of financial firms.

In column 3, we return to examining the effect of $CountryRisk^{NHQ}$, but we additionally control for $FirmRis_{i,t}$. The coefficient remains very stable. What is striking about this result is that this means that within-firm increases in Country Risk are associated with drops in employment and investment by firms based in the country in question *above and beyond* any risk perceptions of the firm itself. Even more striking, the Country Risk measure we are using is "*NHQ*" version, meaning it is entirely a measure of foreign investors perceptions that are covarying negatively with firm-level investment and employment decisions. The coefficient on $CountryRisk^{NHQ}_{c,t}$ in Column 3 implies that a one standard deviation increase in country risk is associated with a 20.1% decrease in the firm's investment rate and a 3.1% decrease in employment growth.

In sum, the evidence is consistent with the view that variation in Country Risk (particularly that as perceived by foreigners) affects real allocations, even when holding constant our measure of firm-level overall risk. One possible explanation for this pattern is of course the country-level variation in asset prices highlighted above: if aggregate variation in Country Risk affects capital flows and asset prices at the country-level, then this variation may well affect the ability of domestic firms to invest and hire, even if their own perception of risk remains unchanged.

5.2. The Transmission of Foreign Risk

Having demonstrated the importance of Country Risk as a driver of firm-level outcomes, we now examine whether *firm-level* perceptions of Foreign Risk also affect these firm level decisions. In particular, we now examine the explanatory power of $ForeignRisk_{i,t}$ as defined in equation (3) for firm-level outcomes.

Column 4 of Table 7 adds $ForeignRisk_{i,t}$ as defined in equation 3 to specification 10. The coefficient on Foreign Risk is negative and statistically highly significant (-0.05, s.e.=0.01 with the log investment rate as outcome), suggesting that specifically foreign risks lower firm-level investment, over and above the effect of other risks unrelated to foreign countries. The transmission of risk across borders thus appears to have real effects on firm-level outcomes.

Though theoretically appealing, this very ambitious specification now measures each foreign country's level of risk with considerable error, based only on the conversation in a single earnings call. Moreover, both $ForeignRisk_{i,t}$ and $FirmRisk_{it}$ mechanically load on the frequency of mentions of synonyms for risk or uncertainty within that same transcript. To reduce measurement error, and to remove any mechanical correlation between the two variables, it may be more appealing to approximate

$$ForeignRisk^{*}_{i,t} = \sum_{c \neq c(i)} CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$$

where $\widetilde{CountryRisk}_{c,t}^{NHQ}$ is the residual from a regression of $CountryRisk_{c,t}^{NHQ}$ on country and time fixed effects.

This variation of Foreign Risk is conceptually similar to our definition in Equation 3, but instead uses a weighted average of Country Risk in each country, where the weights correspond to that particular firm's exposure to risk in each country. Firm-level exposure to each country is measured using Equation 7. For example, consider the effect of a sharp increase in Turkey's Country Risk. Suppose there are two firms, one of them frequently refers to Turkish bigrams during its conference calls, but another firm rarely refers to Turkey. Then we will record a sharp increase in the Foreign Risk of the firm exposed to Turkey but little to no increase in the Transmission Risk of the firm that rarely refers to Turkey.

In column 5 of Table 7, we instead add ${ForeignRisk^*}_{i,t}$ as an explanatory variable for firm-level investment alongside foreign perceptions of domestic risk ($CountryRisk_{c(i),t}^{NHQ}$) and total firm-level risk $FirmRisk_{i,t}$. We find that elevated levels of perceived Foreign Risk at the firm level are again associated with depressed levels of hiring and investment. In column 5, we further tighten the specification to look within country-year by including $Country \times Year$ fixed effects. These fixed effects fully absorb $CountryRisk_{c(i),t}^{NHQ}$, yet the coefficient estimates on Foreign Risk remain largely unchanged. In column 6, we additionally show that controlling for $FirmRisk_{i,t}$ or not has little effect on the coefficient of interest. The estimate (-0.057, s.e.=0.010) implies that a one standard deviation increase in the firm's Foreign Risk reduces its investment rate by 5.7% – an effect quantitatively similar to that of other (overall) firm risk (-0.039, s.e.=0.007).

In column 7 we re-estimate the last specification, but include only firms with US headquarters in the regression. The coefficients estimated in this sub-sample tend to be somewhat larger than those in columns 6: We find that a one standard deviation increase in $ForeignRisk_{i,t}^*$ is associated with 11.1% decrease in the investment rate. All estimates remain statistically significant at the 1% level in this sub-sample of US firms.

Panel B shows similar results for firm-level employment growth, where increases in Foreign Risk are now clearly associated with decreases in hiring. The most demanding specification in column 6 implies that a one standard deviation increase a firm's foreign risks is associated with a 0.8% decrease in hiring. Crises abroad and fluctuations in risk associated with foreign countries thus appears to significantly affect firm-level outcomes in the United

States in a manner predicted by canonical theory.

There are potentially other ways to quantify Foreign Risk, and we explore them in detail in Table 8. In particular, we consider versions where instead of using our text-based Exposure weights, we construct alternative measures of Foreign Risk that use firm-level accounting data to weight the various countries. In the first alternate specification, examined in columns 2 and 3, we measure exposure to a given foreign country as the share of a firm's subsidiaries based in a particular country using the 2016 data from Orbis. For instance, if an American firm has 4 subsidiaries, one of which is in Canada and three of which are in Mexico, the weighting $ShareOrbisLinks_{i,CAN}$=0.25 and $ShareOrbisLinks_{i,MEX}$=0.75. While the sign is negative on this alternative version of Foreign Risk, it is statistically significant. In Columns 4 and 5, we replace our exposure weights with information from the Worldscope Geographic Segment data on the country's sales share, using the share of sales (converted to USD) in a given country as the weight. While the sign continues to be negative and is statistically significant at the 10 and 5 percent level for the investment rate and employment, respectively; however, the size of the coefficient tends to be smaller than on $ForeignRisk^*_{it}$.

The greater explanatory power of $ForeignRisk^*_{it}$ constructed using our text-based exposure measure than accounting measures based on subsidiaries and sales speaks to the idea that the true nature of global interconnectedness is far more complicated that can be gleaned from accounting statements. It suggests a key advantage of measuring firm exposure using information on what the firms themselves discuss during their earnings calls. We expand on this theme below when we use our measures to typify the transmission of risk during crises.

To get some idea of the potential relevance of the international transmission of risk, it is useful to ask how much of the variation in overall firm-risk among our sample firms can be accounted for by Foreign Risk. In particular, we project firm-level risk on Foreign Risk and the risk associated with firm i's home country

$$FirmRisk_{it} = \alpha + \beta_i ForeignRisk^*_{i,t} + \gamma_i CountryRisk^{NHQ}_{c(i),t} + \epsilon_{i,t}.$$

We find that the incremental R^2 of the former variable is 18%, while both variables jointly account for 34% of the variation. That is, on average, risks transmitted from foreign countries collectively account for about as much of the variation in a firm's overall risk as does its own-country risk. It is thus perhaps not surprising that we have the statistical power to disentangle the marginal effects of these three types of risk on firm-level outcomes.

6. The Transmission of Country Risk

Having studied the firm-level impact of foreign risks, we now turn to understanding the pattern of transmission of risks around the world more generally. We begin by examining the average flow or risks from a given origin country to a given destination country as defined in Equation 4, which we refer to as Transmission Risk. We then examine how different types of crises deviate from this usual pattern by comparing average transmission to that in a given historical circumstance as defined in Equation 5.

6.1. The Average Transmission of Country Risk

In Table 9, we zoom out from the firm-level analysis and look at the top origins and destinations of Transmission Risk for countries around the world. 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 Australia worrying not only about nearby New Zealand but also about the United Kingdom. In Appendix Table 5 we confirm this conjecture more systematically. Building on a large literature in trade and international finance, we run a gravity regression of bilateral Transmission Risk. With source and destination fixed effects, we find that distance, geographical contiguity, common official language, and a historical colonial relationship are all significant explanatory factors for the transmission of global risk.

To add texture to this analysis, Table 10 decomposes the aggregate flow of risk to the United States by showing the top five origins of transmission risk for ten sectors within the United States. The third column of the table lists the firm in the S&P 500 with the largest transmission risk from each origin as an example. We can observe a large degree of heterogeneity in the countries driving transmission to the US by industry.

For example, major source countries of transmission risk for firms in the US technology sector are Canada, Japan, Ireland, China, and Israel; while firms in the US energy sector are concerned with risks associated with Canada, Mexico, Saudi Arabia, and Venezuela.

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 conventional and unconventional oil resources in the country that it acquired in the 1990s and has been selling off in recent years. Schlumberger provides services for oil exploration, drilling, and production in Saudi Arabia, and has recently opened a manufacturing facility there. Exxon Mobil's activities in Nigeria include exploration for oil and deepwater production, while Conoco Philips is involved in litigation trying to claw back assets expropriated in Venezuela.

6.2. Crisis Transmission

Table 9 showed some of the complex links underlying the usual pattern of transmission. These heterogeneous links raise the possibility that crises transmit in different ways. In this section, we classify crises according to their transmission pattern and explore drivers of heterogeneity in crisis transmission.

We begin by classifying whether crises were transmitted primarily through financial or non-financial sector firms, building on the analysis in Section 4. To do so, we begin by defining the difference in Transmission Risk to a firm during a given crisis and its non-crisis mean,

$$TransmissionRisk^{Difference}_{o\to i,\tau} \equiv TransmissionRisk_{o\to i,\tau} - \overline{TransmissionRisk}_{o\to d,t\notin S^c} \tag{11}$$

where i indicates a particular firm. We then run a regression of this variable on a constant a dummy whether firm i is a financial firm:

$$TransmissionRisk^{Difference}_{o\to i,\tau} = \alpha_{o\to i,\tau} + \alpha^{Fin}_{o\to i,\tau}\mathbb{1}_{Fin} + \epsilon_{o\to i,\tau} \tag{12}$$

.

where $\mathbb{1}_{Fin}$ is an indicator for whether firm i is a financial firm. If $\alpha_{o\to i,\tau}$ is positive, then we know that during the crisis, financial firms saw their transmission risk from country o increase relative to their firm-level benchmark more than did non-financial corporates. In Column 4, we classify a crisis as "Fin" if $\alpha_{o\to i,\tau}$ is significantly positive as the 5% level.

We classify crises as "NFC" if $\alpha_{o\to i,\tau}$ is significantly negative, indicating that non-financial corporates saw their transmission risk increase relatively more. If $\alpha_{o\to i,\tau}$ is not statistically significantly different from zero, we classify the crisis as not having a differential transmission pattern. Of our 33 crises, we classify 7 as propagating primary through financial firms and 12 through non-financial corporates. In Column 3 we report the relative financial transmission as the ratio of $\alpha^{Fin}_{o\to i,\tau}/(\alpha_{o\to i,\tau}$, which gives the ratio of transmission in the financial sector relative to the non-financial corporate sector. We can see a large degree of heterogeneity here, with financial firms twice as affected as non-financial firms by Grexit, but affected half as much as non-financial corporates by the start of the Coronavirus pandemic.

We next move from this firm-level metric to exploring the transmission of crises across countries. We construct separate measures of $TransmissionRisk_{o\to d,\tau}$ for each of the crises listed in Figure 2 for each recipient country. We then compare the pattern of transmission during each crisis with the usual pattern of transmission from that origin country by averaging origin-to-destination-specific transmission risk from that origin country across all other (non-crisis) periods. We run the following regression,

$$TransmissionRisk_{o\to d,\tau} = \alpha_{o,\tau} + \beta_{o,\tau}\overline{TransmissionRisk}_{o\to d,t\notin S^c} + \epsilon_{o\to d,\tau}, \tag{13}$$

where S^c is the set of time periods during which country c is in crisis. This regression will help us measure the global impact of a crisis, the bilateral transmission strength, and the regularity of the crisis transmission pattern.

We measure the Global Impact of a crisis as follows:

$$GlobalImpact_{\tau} = \widehat{\alpha_{0,\tau}} + \widehat{\beta_{o,\tau}} \cdot \overline{TransmissionRisk}^{Median}_{o\to d,t\notin S^c} \tag{14}$$

In other words, we take the predicted value of transmission risk for the country with the median average transmission risk.[23] This measures how much risk is transmitted to the median country during a crisis and is reported in Column 2 of Table 11, with the ordering or

[23] We prefer to use the median rather than the mean because the distribution is skewed right.

crises corresponding to this measure of their global impact. Immediately, we can see that the measure delivers a sensible ranking, with 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 Global Financial Crisis in the United States from 2008q1-2008q3. Figure 6 Panels (A) and (B) plots the transmission risk during these two crises against transmission risk in normal times emanating from the United States and China. In both cases, we observe large increases in Transmission Risk to all countries, consistent with our classification of them as the crises with the largest global impact. While large countries dominate the top of the rankings (with Japan, China, and the United States occupying the next 5 spots), we see that Mexican trade war, Thai floods, and Russia's Crimean Crisis follow.

We next turn to how each crisis was transmitted across countries. The regression coefficients $\beta_{o,\tau}^{Level}$ are reported in Column 5 of Table 11. A coefficient above 1 indicates that a given crisis is transmitted relatively more to countries that are generally more exposed to a given country. A higher β means that countries that generally have more risk transmitted from the crisis origin country see even larger increases in their risk than countries generally less exposed. Because a coefficient of 1 indicates unchanged transmission relative to normal times, the hypothesis testing in column 5 is relative to this economically meaningful benchmark rather than zero. In Panels (c) and (d) of Figure 6, we plot the two of the 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 always more exposure to Thailand during non-crisis times. Turning to the text snippets, we see that these countries discuss the supply chain disruptions emanating from the Thai floods.[24] Countries generally less exposed to Thailand, by contrast, discuss risk propagating from the floods dramatically less. It is in this sense that the regression identifies the bilateral transmission strength of the crisis. Similarly, looking at the pattern of risk during the start of the Greek crisis, we see huge increases in Transmission Risk to firms based in other euro area countries, yet little propagation to countries less exposed to Greece. This pattern is in strong contrast to the pattern seen above for the start of the Global Financial

[24]For instance, on the December 9, 2011 earnings call of March Networks Corp., there is a discussion ofthe "risk of supply constraints resulting from the recent flooding in Thailand."

Crisis. In this case, all countries essentially saw their risk emanating from the United States increasing about the same amount, regardless of initial exposure to the United States. In this sense, the bilateral transmission of the Global Financial Crisis was very low, with initial exposure to the United States saying very little about the increase in transmission risk.

Finally, we turn analyzing the regularity of the pattern of transmission risk during crises. To do so, we examine the pattern of the R^2 in the level and difference regression. The R^2 measures whether the cross-country pattern of transmission risk is similar to the pattern during non-crisis times. Panels of Figure 6 (e) and (f) 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 that the countries generally most exposed to Hong Kong, such as Singapore, Malaysia, China, and Taiwan, see large increases in risk, with less exposure countries such as The United States, seeing relatively small increases. Importantly, there are essentially no exceptions to this pattern, generating a high R^2 (0.95) and letting us classify the crisis as having a relatively regular transmission pattern. We contrast that with Fukushima in Panel (f) 6, the crisis with the lowest $R^2_{o,\tau}$ in our sample (0.32).[25] The plot shows relatively large dispersion and unusually large impacts in Germany and Taiwan, among others. Systematically examining high-impact snippets of text from German firms reveals the reason: The Fukushima disaster was the ultimate catalyst for the end of 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 whatsoever. Other outliers are attributable to the unusual effects this event had on supply chains, fishing, and the insurance industry, among others.

6.3. Heterogeneity in Crises

Having demonstrated how we classify crisis characteristics using our data, we turn to exploring the drivers of this crisis heterogeneity. Specifically, we classify crises into four overlapping groups: Emerging Market crises, Natural Disasters, Sovereign Debt crises, and Political Instability. We classify the crises manually, we do so by utilizing the the firm-level text

[25] For a detailed analysis of this event also see Boehm et al. (2019), Hassan et al. (2020), and Carvalho et al. (2021).

classifications constructed in Figure 2. For emerging markets, we include all crises in Brazil, China, Egypt, Mexico, Russia, Thailand, and Turkey. The crises classified as natural disasters are the Thai Floods, Fukushima, and the start of the Coronavirus pandemic. Sovereign debt crises include all three Greek Crises, the S&P downgrading of the United States government, Ireland, Spain and Italy during the European Sovereign Debt crisis, and the Turkish crisis from 2018q4 to 2019q1 we classify based on text-snippets as a "Currency and Debt Crisis."[26] Finally, we classify crises of "Political Instability" as the coup attempt against President Erdogan in Turkey, the Brazilian corruption scandal of 2015-6, the Thai military coup of 2014, the Egyptian Revolution in 2011, the Iranian Green Revolution, and the Hong Kong Protests of 2019.

In Table 12, we regress our 4 crisis properties from Table 11 on dummies for these four different types of crises. A number of striking patterns emerge. First, in column 1 we see that emerging market crises and natural disasters propagate primarily through non-financial corporate firms. Our finding is distinct from the well-known narrative is that emerging market crises are *driven* by financial risks. This could still be true, however our finding is distinct in showing that it is non-financial corporate firms that *perceive* more elevated risk during emerging market crises. By contrast, the risk from sovereign debt crises overwhelmingly concern financial firms, with their transmission risk %72 higher than non-financial corporates. Second, during our sample period, we find that sovereign debt crises and political instability had smaller global impacts than did natural disasters, with the latter being driven primarily by the large spike in risk at the beginning of the pandemic. Third, we see that natural disasters and sovereign debt crises have a strong bilateral transmission pattern, with countries more exposed to these countries in normal time experiencing significantly more transmission risk during a crisis. Finally, we see no significant differences in regularity across crises.

In sum, our measures of transmission risk yield a useful characterization of how the transmission of risks during a given crisis differs from the regular flow of risk during non-crisis times. These measures capture the spirit of the Forbes and Rigobon (2002) definition of contagion: "a significant increase in cross-market linkages after a shock to one country."

[26] Although it concerned government debt, we did not include the S&P downgrade of the United States because the loss of AAA status seemed qualitatively different than crises concerning outright default risk.

7. Country Risk, Global Risk, and Exchange Rates

In this final section, turn to our fourth measure, Global Risk, to revisit the link between exchange rates and risk. A large literature in international macroeconomics (Meese and Rogoff (1983), Rossi (2013)) has found that traditional fundamentals that canonical models say should explain exchange rate movements are largely disconnected from currency movements in the data. A growing literature in international finance (Lustig et al. (2011), Lustig et al. (2014), Avdjiev et al. (2019), Jiang et al. (2018), Verdelhan (2018), and Lilley et al. (2019)) has instead focused on explaining exchange rate movements conditional on movements in global risk factors constructed from asset prices. This literature has shown ample evidence of a factor structure in exchange rates, with some exchange rates loading more or less on variation in these global risk factors. However, a remaining challenge in this literature is that the majority of the existing evidence is internal to asset prices, effectively explaining variation in exchange rates with risk factors that are themselves constructed from variation in asset prices. In this section, we explore the hypothesis that exchange rates fluctuate in response to changes in risk directly using our measures of country and global risk. That is, rather than using factors constructed from asset returns, we relate exchange rate movements to variation in our text-based measures of risk – relying on texts generated by global investors and executives.[27]

We begin in Table 13 with a panel regression framework, examining the ability of changes in our country risk and sentiment measures to explain changes in the quarterly exchange rate against the USD. In column 1, we run a univariate regression (conditional on country fixed effects) of changes in exchange rates on country risk and find that a one log point increase in country risk is associated with a 0.13 log point depreciation of the country's currency against the USD.[28] That is, currencies generally tend to depreciate against the US dollar when their countries become riskier. The regression in column 2 then adds the change in global risk. Consistent with the conventional view that the US dollar is a "safe haven" currency, we find that when global risk increases, all currencies tend to depreciate against the the US dollar (the base currency in this regression). In columns 3 through 5, we introduce year-quarter fixed effects, thereby absorbing the common variations through GlobalRisk. We see

[27] Kalemli-Özcan and Varela (2021) examine the relationship between the failure of UIP and risk measures.
[28] We use Germany's country risk for the euro and drop data on all other euro area currencies.

that increases in country risk continue to coincide with depreciations of the local currency against the USD in the panel. Column 4 controls for changes to country-specific sentiment, and shows that rises in country-specific sentiment additionally correlate with appreciations. Finally, in column 5, we ask whether it is truly country-specific risk that explains these patterns, or whether each country's risk may itself load heterogeneously on global risk, a possibility we cannot exclude despite controlling for time fixed effects. Instead, we run a series of regressions of

$$\Delta log(CountryRisk_{c,t}) = \alpha_c + \beta_c \cdot \Delta log(GlobalRisk_t) + \epsilon_{c,t}$$

and then extract the component of each country's risk that comes from this common loading, $\hat{\beta}_c \cdot \Delta log(GlobalRisk_t)$. In column 5, we control for this variable and continue to find a statistically and economically significant role for country risk in explaining the pattern of bilateral exchange rate changes against the US dollar.

Having shown the significant explanatory power of country risk and sentiment for changes in exchange rates, we now return to the question of the explanatory power of heterogeneous loadings on global risk. In particular, we run a regression of the form

$$\Delta e_{c,t} = \alpha_c + \beta_c \cdot \Delta log(GlobalRisk_t) + \epsilon_{c,t}$$

where $\Delta e_{c,t}$ is the period-average change in the equal-weighted broad exchange rate.[29] We move from the bilateral exchange rate to a broad exchange rate to more easily see whether currencies tend to appreciate or depreciate relative to all other currencies in response to spikes in global risk. Panel A of Figure 8 plots these β coefficients for each of the currency-specific regressions with standard error bands. We see a large degree of heterogeneity across countries, providing direct evidence for the heterogeneous loading of currencies on global risk. In Panel B of Figure 8, we plot these estimated β_c coefficients on the x-axis and the R^2 of the regression on the y-axis. We plot in gray the currencies that are relatively more managed or even pegged during the sample period.[30] We see that traditionally "risky" currencies,

[29] Aloosh and Bekaert (2019) discuss the advantages of using the equal-weighted broad exchange rates, or "currency baskets."

[30] We use the de facto exchange rate classifications from Ilzetzki et al. (2019). We report currencies in green if the average Ilzetzki et al. (2019) rating from 2003 to the present averages at least a 12 in their "fine"

such as emerging market currencies like the Mexican peso and South African Rand as well as the carry currencies like the Australian dollar, have large negative betas on global risk, meaning they significantly depreciate when global risk increases. By contrast, among the floating currencies, it is only the Yen, Dollar, and Euro that have their broad exchange rate load positively on global risk. That is, these three "safe haven" currencies appreciate when risks as perceived by global investors and executives are high.

In panels (C) and (D) of Figure 8, we provide direct evidence for the idea that this heterogeneity in the loading on global risk can explain cross-country heterogeneity in nominal interest rates and excess returns. In particular, we see that currencies that depreciate in response to increases in global risk have significantly higher nominal interest rates. In addition, these heterogeneous loadings appear to be a priced risk factor, as those currencies that depreciate in response to spikes in global risk have earned significantly higher excess returns against the USD than do currencies that either appreciate or depreciate less. We view these results as providing direct evidence for theories emphasizing cross-country heterogeneity in loadings on global risk as explaining persistent differences in interest rates and excess returns across currencies (i.e. Lustig et al. (2011), Lustig et al. (2014), Verdelhan (2018), Hassan (2013) and Richmond (2019)).

8. Conclusion

We present a methodology for measuring country risk at the micro-level and aggregating to the macro-level using natural language processing of conference call transcripts of firms around the world. By beginning with the firm-level measurements, we are able not just to construct consistent measures of aggregate country risk, but to explore the sources and transmission channels of this country risk. While this paper emphasized the connection between country risk and capital flows and understanding of the transmission of risk at the firm and country level, we believe the methodology opens the door to a range of future research questions. The underlying micro data are posted at country-risk.net, allowing researchers to explore a range of questions on global risk perceptions and their consequences.

classification. That means the currencies rank as least "De facto moving band +/-5% Managed floating" and report them in gray. We classify the Euro as floating rather than looking at the individual country classifications.

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Table 1: Top 20 ngrams in the training library of Greece, Turkey, and Japan

Ngram	tf×idf	Frequency	Countries	Ngram	tf×idf	Frequency	Countries
Panel A: Greece							
Greek	607.83	2,897	15	the EA	76.30	119	1
Greece*	607.83	n/a	n/a	The ND	73.09	114	1
Athens	339.67	640	2	New Democracy	69.88	109	1
Hellenic	249.73	649	5	Greeks	64.76	101	1
ND government	130.15	203	1	gov gr	61.55	96	1
Piraeus	127.91	241	2	Strategic Reference	61.55	96	1
Share sale	88.48	138	1	Attica	59.63	93	1
an AE	80.78	126	1	ministerial decisions	59.20	127	3
Thessaloniki	80.67	152	2	Alpha Bank	58.34	91	1
by Law	79.83	511	21	objective value	57.70	90	1
Panel B: Turkey							
Turkey*	805.22	n/a	n/a	an AS	88.63	129	3
Turkish	805.22	2,738	16	the Undersecretariat	87.61	112	2
Gazette No	246.57	398	4	Izmir	82.21	87	1
Turk Eximbank	171.04	181	1	the Directive	76.56	135	5
Ankara	144.58	153	1	in prioritydevelopment	76.54	81	1
Official Gazette	131.89	495	18	prioritydevelopment regions	74.65	79	1
of Turkeys	128.48	187	3	in Turkeys	73.71	78	1
Istanbul	127.94	244	6	Undersecretariat of	71.18	91	2
the lira	114.34	121	1	Region VI	71.18	91	2
the GDFI	94.50	100	1	Patent Institute	70.01	113	4
Panel C: Japan							
Japan*	244.15	n/a	n/a	Standards Law	83.63	206	3
Economy Trade	215.39	466	2	Japanese	81.27	3,801	48
the JFTC	207.15	371	1	Tokyo	81.13	626	22
Health Labour	138.47	248	1	Antimonopoly Law	78.70	215	4
Industry METI	136.24	244	1	Labour Standards	75.78	207	4
the METI	115.58	207	1	AntiMonopoly Law	73.89	182	3
The JFTC	107.21	192	1	inhabitant tax	73.49	159	2
the JPO	86.55	155	1	Okinawa	72.03	129	1
the Diet	85.99	154	1	and Welfare	70.96	246	7
enterprise tax	84.59	183	2	Osaka	69.42	171	3

Notes: This table lists the top 20 ngrams when sorted on *tf×idf* in the training library for three selected countries. Column 2 shows the *tf×idf* 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*); column 3 shows the frequency of the ngram in the country-specific library; and column 3 shows the number of country libraries with that ngram. A country-specific training library consists of (1) all adjacent two-word combinations (bigrams) from the country's Economist Country Commerce Reports published between 2002 and 2019; (2) all unigrams and bigrams from the country-specific Geonames list of country names, region names, and city names of cities with more than 15,000 inhabitants in 2018; and (3) all adjectival demonymic forms of the country name from Wikipedia and the CIA World Factbook.

Table 2: Country Exposure correlates positively with measures of firm links

	$Exposure_{i,c}$ (*std.*)				
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(Headquarter)_{i,c}$	2.590***			2.424***	3.202***
	(0.044)			(0.084)	(0.111)
$\mathbb{1}(Segment\ sale\ link)_{i,c}$		1.413***		1.117***	1.301***
		(0.027)		(0.027)	(0.031)
$\mathbb{1}(Subsidiary)_{i,c}$			0.648***	0.285***	0.325***
			(0.009)	(0.007)	(0.008)
R^2	0.113	0.064	0.059	0.168	0.205
N	664,440	268,856	387,225	168,840	168,840
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 3. Column 4 includes country fixed effects. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 3: Summary statistics

Panel A: Firm-country	Mean	Median	St. Dev.	Min	Max	N
$CountryExposure_{i,c}$ *(std.)*	0.79	0.66	1.00	0.00	89.64	664,440
$\mathbb{1}(Headquarter)_{i,c}$	0.02	0.00	0.13	0.00	1.00	664,440
$\mathbb{1}(Segment\ sale\ link)_{i,c}$	0.05	0.00	0.22	0.00	1.00	268,856
$\mathbb{1}(Subsidiary)_{i,c}$	0.16	0.00	0.36	0.00	1.00	387,225
Panel B: Country-quarter	**Mean**	**Median**	**St. Dev.**	**Min**	**Max**	**N**
$CountryRisk^{ALL}_{c,t}$ *(std.)*	3.69	3.50	1.00	2.15	10.11	3,240
$CountryRisk^{NHQ}_{c,t}$ *(std.)*	4.22	4.04	1.00	2.57	11.84	3,240
$CountryRisk^{FIN}_{c,t}$ *(std.)*	3.87	3.70	1.00	2.16	11.72	3,240
$CountryRisk^{NFIN}_{c,t}$ *(std.)*	3.33	3.12	1.00	1.93	9.89	3,240
$CountrySentiment^{ALL}_{c,t}$ *(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
$Total\ inflows_{c,t}$ *(%)*	1.68	1.51	2.25	-16.11	18.62	2,792
$Sovereign\ CDS\ spread_{c,t}$ (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
$\Delta \log spot\ rate_{c,t}$	-0.01	0.00	0.13	-3.66	0.37	2,592
Panel C: Firm-year	**Mean**	**Median**	**St. Dev.**	**Min**	**Max**	**N**
$CountryRisk^{NHQ}_{c(i),t}$ *(std.)*	3.46	3.77	1.01	1.37	5.10	90,355
$CountryRisk^{FIN}_{c(i),t}$ *(std.)*	4.09	4.35	1.01	1.65	5.72	90,355
$CountryRisk^{OWNIND}_{c(i),t}$ *(std.)*	2.72	2.96	1.00	0.57	13.51	90,355
$FirmRisk_{i,t}$ *(std.)*	1.18	0.95	0.97	0.00	17.56	93,759
$\Delta \log(employment\ rate_{i,t})$	0.04	0.02	0.19	-0.71	0.75	70,963
$\log(investment\ rate_{i,t})$	-1.92	-1.89	0.94	-5.04	0.52	74,999
$ForeignRisk^{*}_{i,t}$	2.80	2.63	0.78	0.00	12.72	93,759
$ForeignRisk_{i,t}$	1.01	0.74	1.00	0.00	17.13	93,759

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, B, and C show the relevant statistics for the regression sample at the firm-country, country-quarter and firm-year 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 $\mathbb{1}(Headquarter)_{i,c}$, $\mathbb{1}(Segment\ data\ link)_{i,c}$, $\mathbb{1}(Subsidiary)_{i,c}$ are binary variables equal to one if firm i is headquartered in country c, reports sales to country c, or has a subsidiary in country c, respectively. In Panel B, $CountryRisk^{ALL}_{c,t}$ *(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; $CountryRisk^{NHQ}_{c,t}$ *(std.)*, $CountryRisk^{FIN}_{c,t}$ *(std.)*, and $CountryRisk^{NFIN}_{c,t}$ *(std.)* are the same but based on firms not headquartered in c at t, financial (SIC $\in [6000, 6800)$), and non-financial (SIC $\notin [6000, 6800)$) firms respectively; $CountrySentiment_{c,t}$ *(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; $\overline{FirmRisk_{i,c,t}}_{c,t}$ *(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); $Realized\ MSCI\ volatility_{c,t}$ is the standard deviation of the daily MSCI stock return index for country c during quarter t (based on local currency), $\Delta \log(MSCI\ return\ on\ index_{c,t})$ is the $t-1$ to t change in log of the end-of-quarter 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 percent); $Sovereign\ bond\ yield_{c,t}$ is the end-of-quarter mid yield on a 1-year sovereign bond of country c and quarter t (in percent); and $Real\ GDP\ growth_{c,t}$ is the quarter-to-quarter percent change in real GDP of country c and quarter t. In Panel C, $CountryRisk^{NHQ}_{c(i),t}$ *(std.)* is Country Risk of the country of headquarter of firm i, $c(i)$, in year t as perceived by firms without headquarter in country c, normalized by its standard deviation in the panel; $FirmRisk_{i,t}$ *(std.)* is the number of risk words per word mentioned in any earnings call of firm i in year t; $\Delta \log(employment\ rate_{i,t})$ is the year-to-year difference in the log of employment, winsorized at the first and last percentile; $\log(investment\ rate_{i,t})$ is a the log of investment rate, which is calculated recursively using a perpetual-inventory method and winsorized at the first and last percentile; $ForeignRisk^{*}_{i,t}$ *(std.)* is the weighted sum over countries of residualized $CountryRisk^{NHQ}_{c,t}$ with weights given by the firm's Country Exposure to country c in quarter t, $CountryExposure_{i,c,t}$, normalized by its standard deviation in the firm-year panel; and $ForeignRisk_{i,t}$ *(std.)* is the sum over countries of $CountryRisk_{i,c,t}$, normalized by its standard deviation in the firm-year panel.

Table 4: Country Risk, Country Sentiment, and Stock Market Return and Volatility

	MSCI equity return$_{c,t}$		Δ*Realized volatility*$_{c,t}$	
	(1)	(2)	(3)	(4)
$\Delta\log(CountryRisk^{ALL}_{c,t}\ (std.))$	–0.399***	–0.285***	0.098***	0.110***
	(0.045)	(0.041)	(0.018)	(0.022)
$\Delta\log(CountrySentiment^{ALL}_{c,t}\ (std.))$		0.190***		0.008
		(0.034)		(0.006)
R^2	0.099	0.230	0.015	0.018
N	2,918	2,914	2,917	2,913

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are as defined in Table 3. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 5: Drivers of Capital Flows and Sovereign Default Risk

Panel A	*Total inflows*$_{c,t}$ *(%)*				
	(1)	(2)	(3)	(4)	(5)
$CountryRisk^{ALL}_{c,t}$ *(std.)*		–0.759***	–0.735***	–0.647***	–0.351**
		(0.188)	(0.182)	(0.144)	(0.170)
$GlobalRisk_t$ *(std.)*	–0.034***	–0.017**	–0.017**		
	(0.006)	(0.008)	(0.008)		
Real GDP growth$_{c,t}$			–0.008	0.023**	0.022**
			(0.008)	(0.010)	(0.010)
$CountrySentiment^{ALL}_{c,t}$ *(std.)*					0.757***
					(0.234)
R^2	0.105	0.119	0.125	0.269	0.281
N	2,792	2,792	2,657	2,657	2,657
Panel B	Δ *CDS spread*$_{c,t}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \log(CountryRisk^{ALL}_{c,t}$ *(std.)*$)$		2.410***	2.230**	2.294***	2.281***
		(0.835)	(0.851)	(0.826)	(0.821)
$\Delta \log(GlobalRisk_t$ *(std.)*$)$	7.692***	5.266***	4.646***		
	(1.845)	(1.450)	(1.346)		
Real GDP growth$_{c,t}$			–0.005	–0.001	–0.001
			(0.004)	(0.004)	(0.004)
$\Delta \log(CountrySentiment^{ALL}_{c,t}$ *(std.)*$)$					–0.473
					(0.341)
R^2	0.070	0.085	0.079	0.158	0.161
N	2,626	2,626	2,444	2,444	2,440
Country FE	yes	yes	yes	yes	yes
Year-quarter FE	no	no	no	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are defined as in Table 3. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 6: Decomposing Country Risk

PANEL A	Total inflows$_{c,t}$ (%)							Portfolio$_{c,t}$ (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CountryRisk^{ALL}_{c,t}$ (std.))	–0.700***							
	(0.159)							
$CountryRisk^{US\ firms}_{c,t}$ (std.))		–0.863***						
		(0.214)						
$CountryRisk^{NHQ}_{c,t}$ (std.))			–0.541***	–0.496***	–0.511***	–0.518***		
			(0.190)	(0.170)	(0.181)	(0.190)		
$\overline{\text{FirmRisk}}_{i,t_{c,t}}$ (std.))				–0.179*				
				(0.090)				
$CountryRisk^{HQ}_{c,t}$ (std.))					0.010			
					(0.074)			
$WUI_{c,t}$ (std.))						–0.094*		
						(0.055)		
$CountryRisk^{FIN}_{c,t}$ (std.))							–0.468***	–1.109**
							(0.102)	(0.424)
$CountryRisk^{NFC}_{c,t}$ (std.))							–0.291*	0.006
							(0.165)	(0.260)
R^2	0.251	0.247	0.248	0.332	0.275	0.249	0.254	0.134
N	2,792	2,792	2,792	2,079	2,589	2,792	2,792	2,936

PANEL B	Δ CDS spread$_{c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta\log(CountryRisk^{ALL}_{c,t})$ (std.))	2.418***						
	(0.789)						
$\Delta\log(CountryRisk^{US}_{c,t})$ (std.))		2.287***					
		(0.827)					
$\Delta\log(CountryRisk^{NHQ}_{c,t})$ (std.))			2.430***	1.971***	2.324***	2.187**	
			(0.756)	(0.680)	(0.777)	(0.847)	
$\Delta\log(\overline{FirmRisk}_{i,t_{c,t}})$ (std.))				0.200*			
				(0.115)			
$\Delta\log(CountryRisk^{HQ}_{c,t})$ (std.))					0.057*		
					(0.032)		
$\Delta\log(WUI_{c,t})$ (std.))						0.057*	
						(0.033)	
$\Delta\log(CountryRisk^{FIN}_{c,t})$ (std.))							0.751*
							(0.399)
$\Delta\log(CountryRisk^{NFC}_{c,t})$ (std.))							1.657***
							(0.595)
R^2	0.165	0.161	0.163	0.147	0.169	0.163	0.164
N	2,626	2,626	2,626	1,906	2,330	1,866	2,626

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are defined as in Table 3. 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% level, respectively.

Table 7: The Transmission of Country Risk

	All firms						US firms
Panel A	$\log(investment\ rate_{i,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ForeignRisk^{*}_{i,t}$ *(std.)*					–0.060***	–0.057***	–0.111***
					(0.011)	(0.010)	(0.017)
$ForeignRisk_{i,t}$ *(std.)*				–0.050***			
				(0.007)			
$CountryRisk^{NHQ}_{c(i),t}$ *(std.)*	–0.204***		–0.201***	–0.200***	–0.205***		
	(0.022)		(0.022)	(0.022)	(0.022)		
$CountryRisk^{FIN}_{c(i),t}$ *(std.)*		–0.212***					
		(0.025)					
$CountryRisk^{OWNIND}_{c(i),t}$ *(std.)*		–0.029*					
		(0.015)					
$FirmRisk_{i,t}$ *(std.)*			–0.043***			–0.039***	–0.050***
			(0.007)			(0.007)	(0.010)
R^2	0.511	0.511	0.512	0.512	0.512	0.525	0.499
N	71,673	71,673	71,673	71,673	71,673	73,771	47,186
Panel B	$\Delta\log(employment_{i,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ForeignRisk^{*}_{i,t}$ *(std.)*					–0.010***	–0.008***	–0.019***
					(0.002)	(0.002)	(0.003)
$ForeignRisk_{i,t}$ *(std.)*				–0.008***			
				(0.001)			
$CountryRisk^{NHQ}_{c(i),t}$ *(std.)*	–0.032***		–0.031***	–0.031***	–0.032***		
	(0.005)		(0.005)	(0.005)	(0.005)		
$CountryRisk^{FIN}_{c(i),t}$ *(std.)*		–0.029***					
		(0.005)					
$CountryRisk^{OWNIND}_{c(i),t}$ *(std.)*		0.005					
		(0.004)					
$FirmRisk_{i,t}$ *(std.)*			–0.009***			–0.009***	–0.011***
			(0.001)			(0.001)	(0.002)
R^2	0.233	0.233	0.233	0.233	0.233	0.244	0.236
N	67,266	67,266	67,266	67,266	67,266	69,509	45,775
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	n/a	yes
Country×Year FE	no	no	no	no	no	yes	n/a

Notes: This table shows coefficient estimates and standard errors from regressions at the firm-year level. All variables are defined as in Table 3. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 8: Comparing $Exposure_{i,c,t}$ and alternative measures of firm-country links in $ForeignRisk_{i,t}$

	log($investment\ rate_{i,t}$)				
	(1)	(2)	(3)	(4)	(5)
$ForeignRisk^{*}_{i,t}$ *(std)*	–0.059***		–0.060***		–0.059***
	(0.010)		(0.010)		(0.010)
$\sum_{c\neq c(i)} ShareOrbisLinks_{i,c} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std.)*		0.043	0.056		
		(0.089)	(0.089)		
$\sum_{c\neq c(i)} SegmentSale_{i,c} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std)*				–0.037**	–0.034*
				(0.018)	(0.018)
R^2	0.525	0.524	0.525	0.524	0.525
N	73,771	73,771	73,771	73,771	73,771
	Δ log($employment_{i,t}$)				
	(1)	(2)	(3)	(4)	(5)
$ForeignRisk^{*}_{i,t}$ *(std)*	–0.008***		–0.008***		–0.008***
	(0.002)		(0.002)		(0.002)
$\sum_{c\neq c(i)} ShareOrbisLinks_{i,c} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std.)*		–0.024	–0.022		
		(0.017)	(0.017)		
$\sum_{c\neq c(i)} SegmentSale_{i,c} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std)*				–0.009**	–0.008**
				(0.004)	(0.004)
R^2	0.244	0.243	0.244	0.243	0.244
N	69,509	69,509	69,509	69,509	69,509
Year FE	n/a	n/a	n/a	yes	yes
Firm FE	yes	yes	yes	yes	yes
Country×Year FE	yes	yes	yes	n/a	n/a

Notes: This table shows coefficient estimates and standard errors from regressions at the firm-year level. $\sum_{c\neq c(i)} \mathbb{1}(ShareOrbisLinks_{i,c}) \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std.)* is defined similarly as $ForeignRisk^{*}_{i,t} := \sum_{c\neq c(i)} CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ but with $\mathbb{1}(ShareOrbisLinks_{i,c})$ replacing $CountryExposure_{i,c,t}$, where $\mathbb{1}(ShareOrbisLinks_{i,c})$ is firm i's equal-weighted share in country c of its subsidiaries in any country. $\sum_{c\neq c(i)} \mathbb{1}(SegmentSale_{i,c}) \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ *(std.)* is defined analogously but instead of a dummy it uses the average sales (in USD) of firm i to country c. The remaining variables are defined as in Table 3. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 9: Top five origins and destinations of transmission risk for selected countries

Firms headquartered in	Worry most about	Firms that worry about	Are headquartered in
United States	Canada	China	Hong Kong
	China		Singapore
	Mexico		Taiwan
	Japan		South Korea
	Brazil		Japan
Canada	United States	Greece	Belgium
	China		Austria
	Mexico		Italy
	Australia		France
	United Kingdom		Spain
United Kingdom	Ireland	Russia	Finland
	China		Austria
	United States		Turkey
	Australia		Denmark
	Spain		Italy
Australia	New Zealand	Brazil	Chile
	China		Spain
	United Kingdom		Mexico
	United States		Norway
	Singapore		France
China	Hong Kong	Turkey	Greece
	United States		Austria
	Japan		Italy
	Taiwan		Russia
	Thailand		South Korea
India	China	United Kingdom	Ireland
	United Kingdom		Australia
	United States		France
	Brazil		Sweden
	South Africa		Denmark
Japan	China	Argentina	Chile
	Thailand		Spain
	United States		Mexico
	Indonesia		Brazil
	India		Italy
Germany	China	Egypt	Greece
	Russia		Turkey
	United States		Italy
	Spain		France
	Turkey		Netherlands
Sweden	Norway	Iran	Turkey
	China		Russia
	Russia		South Africa
	Poland		Japan
	United Kingdom		Greece
Brazil	Argentina	Japan	South Korea
	China		Singapore
	Mexico		Hong Kong
	Colombia		Israel
	United States		Switzerland

Notes: This table lists for ten countries where firms are headquartered (column 1), the top five countries those firms worry most about (column 2); it also lists for ten countries that firms worry about (column 3), the top five countries those firms are headquartered (column 4). The countries in columns 1 and 3 are hand selected from the countries where most firms are headquartered and from the countries with most crises in Table 2, respectively. The rankings in columns 2 and 4 are based on averaging the relevant components in the sum of $ForeignRisk^*_{i,t} := \sum_{c \neq c(i)} CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ for country-country pairs, and sorting the resulting lists. For example, for country-country pair $(c(i), c)$, we take the average over all firms headquartered in country $c(i)$ of the relevant components about country c: $(1/N_{c(i)}) \sum_{i \in c(i), c=c} CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$.

Table 10: Top five origins of transmission risk for ten selected US sectors

Firms in US sector	Worry most about	S&P 500 firm in sector with highest worry
Basic Materials	China	Dow Inc (Chemicals)
	Brazil	Mosaic Co (Chemicals)
	Canada	Dow Inc (Chemicals)
	Mexico	WRKCO Inc (Applied Resources)
	Turkey	Nucor Corp (Mineral Resources)
Consumer Cyclicals	Canada	TJX Companies Inc (Retailers)
	China	Yum! Brands Inc (Cyclical Consumer Services)
	Mexico	Autozone Inc (Retailers)
	Brazil	Whirlpool Corp (Cyclical Consumer Products)
	United Kingdom	Copart Inc (Retailers)
Consumer Non-Cyclicals	Canada	Molson Coors Brewing Co (Food & Beverages)
	Mexico	Walmart Inc (Food & Drug Retailing)
	China	Estee Lauder Companies Inc (Personal & Household Products & Services)
	Brazil	Corteva Inc (Food & Beverages)
	Russia	Philip Morris International Inc (Food & Beverages)
Energy	Canada	Devon Energy Corp
	Mexico	Concho Resources Inc
	Nigeria	Exxon Mobil Corp
	Saudi Arabia	Valero Energy Corp
	Brazil	National Oilwell Varco Inc
Financials and Real Estate	Canada	Kimco Realty Corp (Real Estate)
	United Kingdom	Unum Group (Insurance)
	Greece	State Street Corp (Banking & Investment Services)
	New Zealand	Arthur J Gallagher & Co (Insurance)
	Japan	Aflac Inc (Insurance)
Healthcare	Japan	Edwards Lifesciences Corp (Healthcare Services & Equipment)
	Canada	Laboratory Corporation of America Holdings (Healthcare Services & Equipment)
	China	Agilent Technologies Inc (Healthcare Services & Equipment)
	United Kingdom	Cerner Corp (Healthcare Services & Equipment)
	Israel	AbbVie Inc (Pharmaceuticals & Medical Research)
Industrials	China	A. O. Smith Corp (Industrial Goods)
	Canada	W W Grainger Inc (Industrial Goods)
	Mexico	Kansas City Southern (Transportation)
	Brazil	Fleetcor Technologies Inc (Industrial & Commercial Services)
	Australia	L3Harris Technologies Inc (Industrial Goods)
Technology	China	Qorvo Inc (Technology Equipment)
	Japan	F5 Networks Inc (Software & IT Services)
	Canada	CDW Corp (Software & IT Services)
	United Kingdom	CDW Corp (Software & IT Services)
	Brazil	Fidelity National Information Services Inc (Financial Technology (Fintech) & Infrastructure)
Utilities	Canada	NiSource Inc
	Mexico	Sempra Energy
	United Kingdom	PPL Corp
	New Zealand	Ameren Corp
	Brazil	AES Corp

Notes: This table lists for for nine US sectors (column 1) the country they worry most about (column 2), and the S&P firm in that sector with the highest worry (column 3). The ranking in column 2 is based on averaging the relevant components in the sum for $ForeignRisk^{*}_{i,t} := \sum_{c \neq c(i)} CountryExposure_{i,c,t} \times \widetilde{CountryRisk}^{NHQ}_{c,t}$ for sector-country pairs, and sorting the resulting countries for a given sector. For example, for sector-country pair $\widetilde{(s,c)}$, we take the average over all firms in sector s of the relevant components about country c: $(1/N_{i \in s}) \sum_{i \in s, c=c} CountryExposure_{i,c,t} \times CountryRisk_{c,t}$. The firm with the highest worry in column 3 is obtained similarly. The sector classification is from Thomson Eikon.

Table 11: Transmission of risk during crises

Description	Global impact	Financials or non-financials		Bilateral strength	Regularity
	$\widehat{y}$	$\alpha^{FIN}_{o\to i,\tau}/\alpha_{o\to i,\tau}$	Significant for	$\widehat{\beta}_{o\to d,\tau}$	R^2
China: Start of Coronavirus outbreak (2020q1)	3.68	−0.52	NFC	2.58***	0.905
United States: Lehman; start of GFC (2008q1-08q3)	2.26	−0.08		0.92	0.554
Japan: Fukushima disaster (2011q2-11q3)	2.12	−0.25	NFC	1.91*	0.281
China: US-China trade dispute (2018q4-19q4)	2.08	−0.51	NFC	1.73***	0.924
China: Economic uncertainty (2015q3-16q1)	1.84	−0.37	NFC	1.91***	0.938
United States: S&P downgrade (2011q3-11q4)	1.75	0.24	FIN	1.01	0.762
United States: Deepwater Horizon oil spill (2010q2)	1.63	−0.13		0.93	0.673
China: Risk of downturn (2012q4)	1.54	−0.35	NFC	1.41***	0.964
Greece: Grexit referendum, third bailout (2015q3)	1.49	0.49	FIN	2.82***	0.712
Mexico: Trump, trade risks (2017q1)	1.44	−0.33	NFC	1.45***	0.793
Thailand: Flood disaster (2011q4-12q1)	1.40	−0.23	NFC	4.00***	0.683
Turkey: Attempted coup against Erdogan (2016q3)	1.39	−0.19	NFC	1.44*	0.467
United Kingdom: Brexit referendum (2016q3-16q4)	1.37	0.11	FIN	1.51***	0.857
Russia: Crimean crisis, economic crisis (2014q2-15q4)	1.35	−0.22	NFC	2.68***	0.881
Brazil: Deep recession, political turmoil (2015q1-16q2)	1.28	−0.47	NFC	1.68***	0.915
Venezuela: Aftermath of oil strike (2003q1)	1.18	−0.30	NFC	5.09*	0.304
Greece: Sovereign debt crisis, first bailout (2010q1-10q2)	1.17	0.95	FIN	2.80***	0.734
Turkey: Currency and debt crisis (2018q4-19q1)	1.16	0.17		1.79***	0.628
United Kingdom: Risk of no-deal Brexit (2019q1-20q1)	1.14	0.08		1.17**	0.855
Thailand: Coup d'état by military (2014q3)	1.02	−0.02		1.79***	0.856
Nigeria: Oil workers' strike (2003q2)	1.01	−0.29		1.95	0.380
Russia: Economic uncertainty (2011q4)	1.00	−0.17		1.42***	0.822
Greece: Sovereign debt crisis, second bailout (2011q1-12q3)	1.00	1.09	FIN	3.13***	0.722
Turkey: FX volatility (2019q4)	0.98	−0.20		0.97	0.502
Spain: European sovereign debt crisis, elections (2011q4)	0.97	0.12		1.55***	0.906
Ireland: Brexit (2020q1)	0.97	0.39		0.98	0.751
Spain: Rising government yields, bailout (2012q3-12q4)	0.97	0.16		1.67***	0.884
Turkey: FX volatility (2016q1)	0.96	−0.32		1.08	0.603
Egypt: Egyptian revolution (2011q1-11q2)	0.92	−0.22	NFC	3.49***	0.902
Ireland: European sovereign debt crisis (2011q4)	0.90	1.42	FIN	1.10	0.874
Hong Kong: Protests against extradition bill (2019q3-19q4)	0.85	−0.13		1.49***	0.938
Italy: European sovereign debt crisis (2011q4)	0.80	1.59	FIN	1.26***	0.894
Iran: Green Revolution (2012q1)	0.80	−0.21		1.21	0.579

Table 12: Heterogeneity in Crisis Properties

	α_{Fin}/α	Global Impact	Bilateral Transmission	R^2
	(1)	(2)	(3)	(4)
Emerging Market	–0.327***	0.153	0.767**	0.056
	(0.084)	(0.194)	(0.321)	(0.080)
Natural Disaster	–0.161*	0.830	0.750	–0.085
	(0.087)	(0.496)	(0.514)	(0.124)
Sovereign Debt	0.749***	–0.261	0.694*	0.095
	(0.203)	(0.175)	(0.377)	(0.081)
Political Instability	–0.030	–0.357**	0.114	0.046
	(0.093)	(0.140)	(0.406)	(0.099)
Constant	0.041	1.299***	1.225***	0.692***
	(0.080)	(0.177)	(0.210)	(0.068)
R^2	0.684	0.415	0.188	0.085
N	33	33	33	33

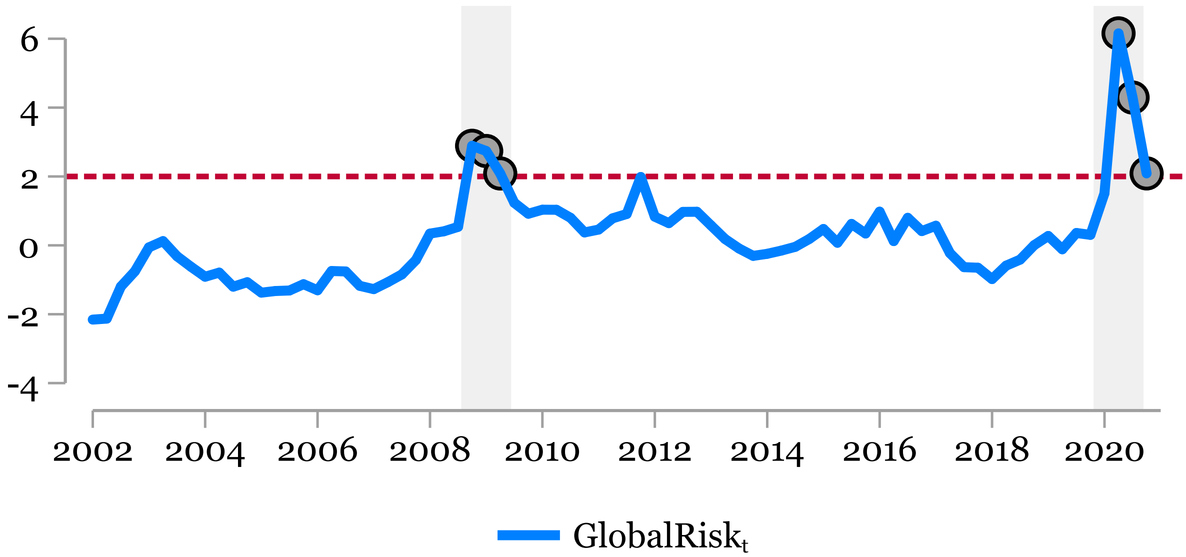
Notes: This table explores whether the key patterns of crisis transmission differ for different types of crises. We consider Emerging Market Crises, Natural Disasters, Sovereign Debt Crises, and Political Instability, with a set included in each category discussed in 6. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 13: Country Risk and Spot Exchange Rates

	$\Delta \log(\mathit{Spot\ rate}_{c,t})$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \log(\mathit{CountryRisk}_{c,t}\ \mathit{(std.)})$	–0.131***	–0.059**	–0.059**	–0.050**	–0.060**
	(0.025)	(0.025)	(0.023)	(0.023)	(0.026)
$\Delta \log(\mathit{GlobalRisk}_{c,t})$		–0.270***			
		(0.056)			
$\Delta \log(\mathit{CountrySentiment}_{c,t}\ \mathit{(std.)})$				0.037*	
				(0.020)	
$\widehat{\beta}_c * \Delta \log(\mathit{GlobalRisk}_t)$					0.071
					(0.282)
R^2	0.151	0.156	0.214	0.214	0.214
N	2,556	2,556	2,556	2,554	2,556
Country FE	yes	yes	yes	yes	yes
Year-quarter FE	no	no	yes	yes	yes

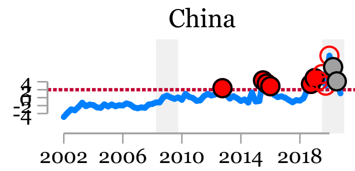
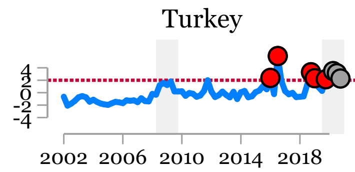
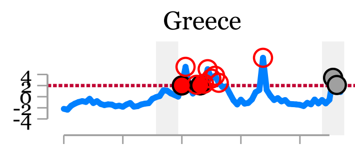
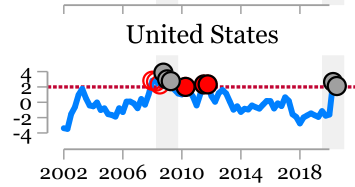
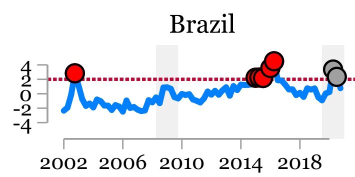
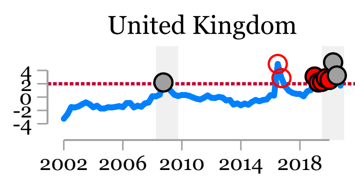
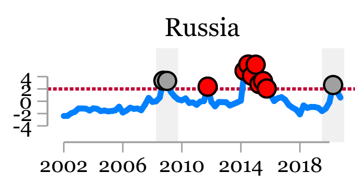
Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are defined as in Table 3. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Figure 1: 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 gray 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.

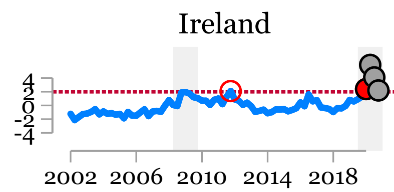
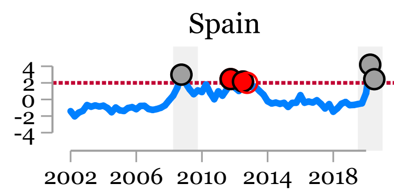
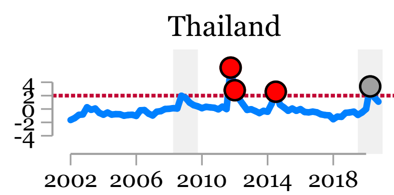
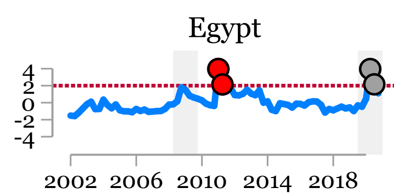
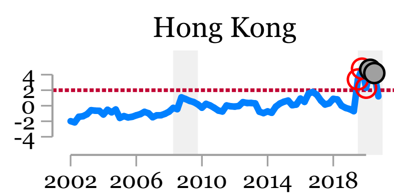
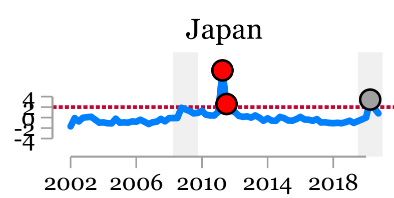
Figure 2: Identifying country crises

Where and when	Description	Time series
China		
2012q4	Risk of downturn	
2015q3-16q1	Economic uncertainty, equity market volatility	
2018q4-19q4	US-China trade dispute	
2020q1	Start of Coronavirus outbreak	
Turkey		
2016q1	FX volatility	
2016q3	Attempted coup against Erdogan	
2018q4-19q1	Currency and debt crisis	
2019q4	FX volatility	
Greece		
2010q1-10q2	Sovereign debt crisis, first bailout	
2011q1-12q3	Sovereign debt crisis, second bailout	
2015q3	Grexit referendum, third bailout	
United States		
2008q1-08q3	Lehman, start of GFC	
2010q2	Deepwater Horizon oil spill	
2011q3-q4	S&P downgrade, uncertainty about fiscal policy	
Brazil		
2002q4	Political uncertainty from elections, economic crisis	
2015q1-16q2	Deep recession, political turmoil	
Great Britain		
2016q3-q4	Brexit referendum	
2019q1-20q1	Risk of no-deal Brexit, general election, Brexit	
Russia		
2011q4	Economic uncertainty	
2014q2-15q4	Oil price drop, Crimean crisis, ruble devaluation, financial crisis	

Global crisis
Local crisis
Local crisis with disproportionate rise among financials

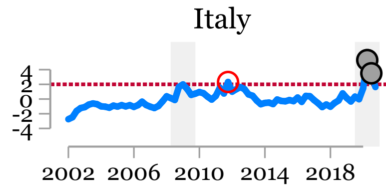
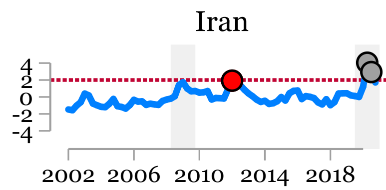
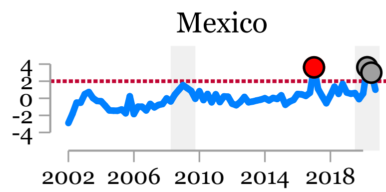
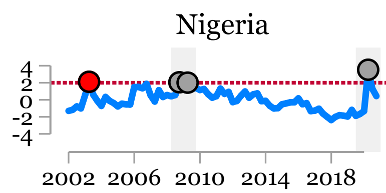
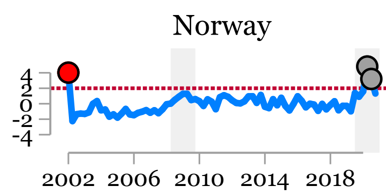
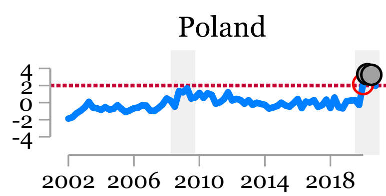
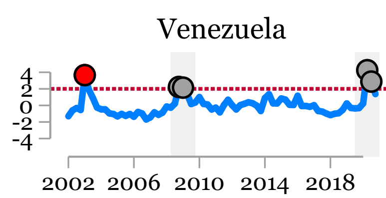
Notes: This table describes and plots country crises based on $CountryRisk_{c,t}$ for the country indicated in column 1. A global crisis is defined as $GlobalRisk_t$ being above two standard deviations (see also Figure 1); a local crisis is defined as the country's $CountryRisk_{c,t}$ being above two standard deviations in the panel (the red horizontal dashed line); and a local crisis with disproportionate rise among financials is defined as a local crisis for which a dummy for financial firms is positive and statistically significant in a firm level regression on the crisis quarter with demeaned $CountryRisk_{i,c,t}$ as the outcome. For Greece, we assume that 2011q2, which is just below the threshold of two standard deviations, is nevertheless part of the crisis that started in 2011q1; similarly for 2015q4 and Brazil. The descriptions are based on reading the highest-ranking snippets from the 30 highest-ranking firms when sorted on Country Risk in the indicated time period.

Figure 2: Identifying country crises (continued)

Where and when	Description	Time series
Ireland		
2011q4	European sovereign debt crisis	
2020q1	Brexit	
Spain		
2011q4	European sovereign debt crisis; elections	
2012q3-12q4	Rising government yields; bailout	
Thailand		
2011q4-12q1	Flood disaster	
2014q3	Coup d'état by military	
Egypt		
2011q1-11q2	Egyptian revolution	
Hong Kong		
2019q3-20q1	Protests against bill allowing extradition to China	
Japan		
2011q2-q3	Fukushima disaster	

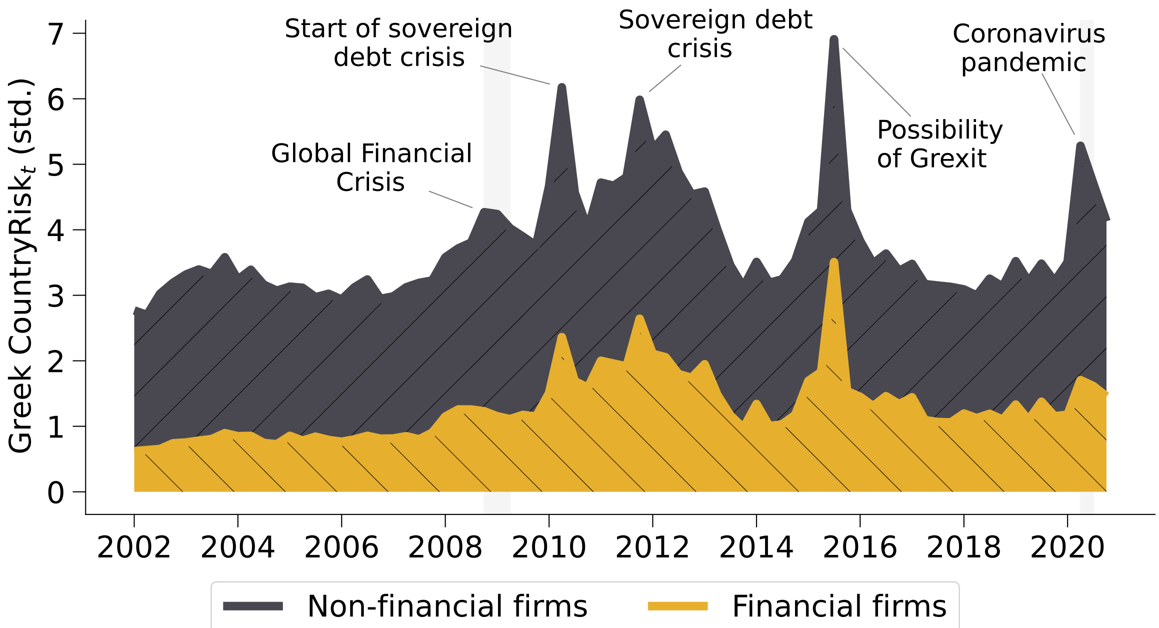
Global crisis
Local crisis
Local crisis with disproportionate rise among financials

Figure 2: Identifying country crises (continued)

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

Global crisis
Local crisis
Local crisis with disproportionate rise among financials

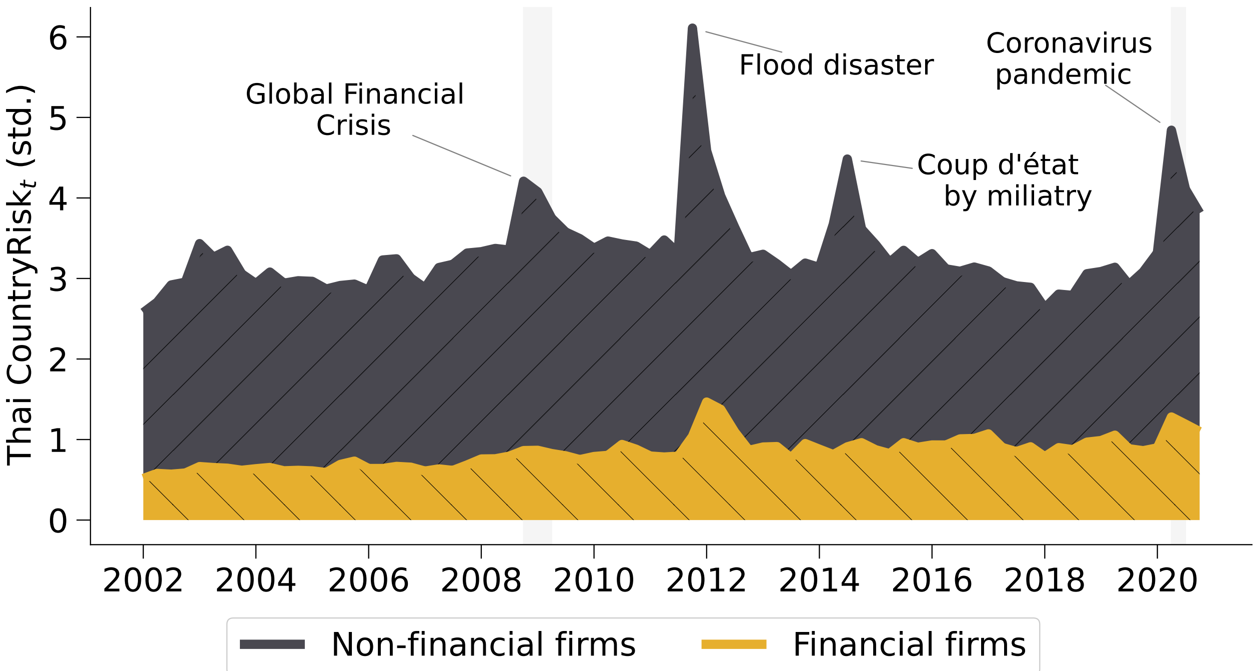
Figure 3: Time series of Greek Country Risk



Summary	Example text excerpts from high-impact snippets
Possiblity of Grexit (2015q3)	"[...] concern related to the possible impact of a Greek eurozone exit has led to persistent volatility in currencies [...]" (BlackRock Inc, July 15, 2015) "[...] we operate in Europe despite the uncertainties you know notably in Greece we are gradually witnessing a gradual acceleration in economic activity [...]" (Societe Generale SA, August 5, 2015)
Start of sovereign debt crisis (2010q2)	"Continued concerns about default risk in Greece and other countries in Europe will only cause more volatility [...]" (Eagle Rock Energy Partners LP, May 6, 2010) "[...] of exposure to banking and sovereign risk in Greece, Italy, Spain, Portugal, and Ireland combined [...]" (National Bank of Canada, May 28, 2010)
Sovereign debt crisis (2011q4)	"[...] the European sovereign debt crisis and the likelihood of a Greek default It is critical that a concerted effort is carried out [...]" (Bankinter SA, October 21, 2011) "[...] 'sovereign debt crisis producing gutwrenching market gyrations The threat of a Greek Spain and Italy default European Bank recapitalizations and financial contagion [...]" (Pzena Investment Management Inc, Oct 26, 2011)

Notes: This figure plots the time series of Greek $CountryRisk_{c,t}$ as defined in equation (2) 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 30 highest-ranked firms when sorted on Country Risk for Greece.

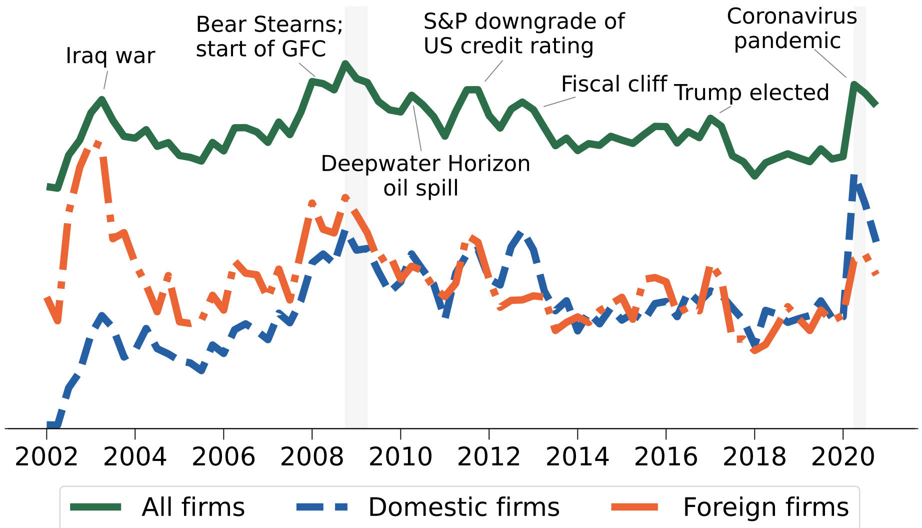
Figure 4: Time series of Thai Country Risk



Summary	Example text excerpts from high-impact snippets
Flood disaster (2011q4-12q1)	"[...] follow the disk drive industry know the ((severe)) flooding in Thailand has created substantial ((disruption)) and uncertainty for the entire hard disk [...] (Hutchinson Technology Inc; November 1, 2011) "[...] about the potential credit impacts of the unfortunate events in Thailand At Scotia Capital I can (assure) you that the variable compensation [...]" (Bank of Nova Scotia; December 2, 2011) "[...] risk of supply constraints resulting from the recent flooding in Thailand Working capital decreased by approximately million to million during the first [...] (March Networks Corp, December 9, 2011)
Coup d'ètat by military (2014q3)	"[...] which accounts for a major proportion of our sales In Thailand sales volume decreased due to political instability following the coup detat [...]" (Mitsubishi Motors Corp; July 30, 2014) "[...] sales and margins However JECs joint venture with Trane in Thailand was negatively affected by the political uncertainty there that has led [...]" (Jardine Matheson Holdings Ltd; August 3, 2014) "[...] the BRICs was offset by losses in other countries including Thailand which was pressured by geopolitical risk On a yeartodate basis we [...] (International Flavors & Fragrances Inc)

Notes: This figure plots the time series of Thai $CountryRisk_{c,t}$ as defined in equation (2) 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 30 highest-ranked firms when sorted on Country Risk for Thailand.

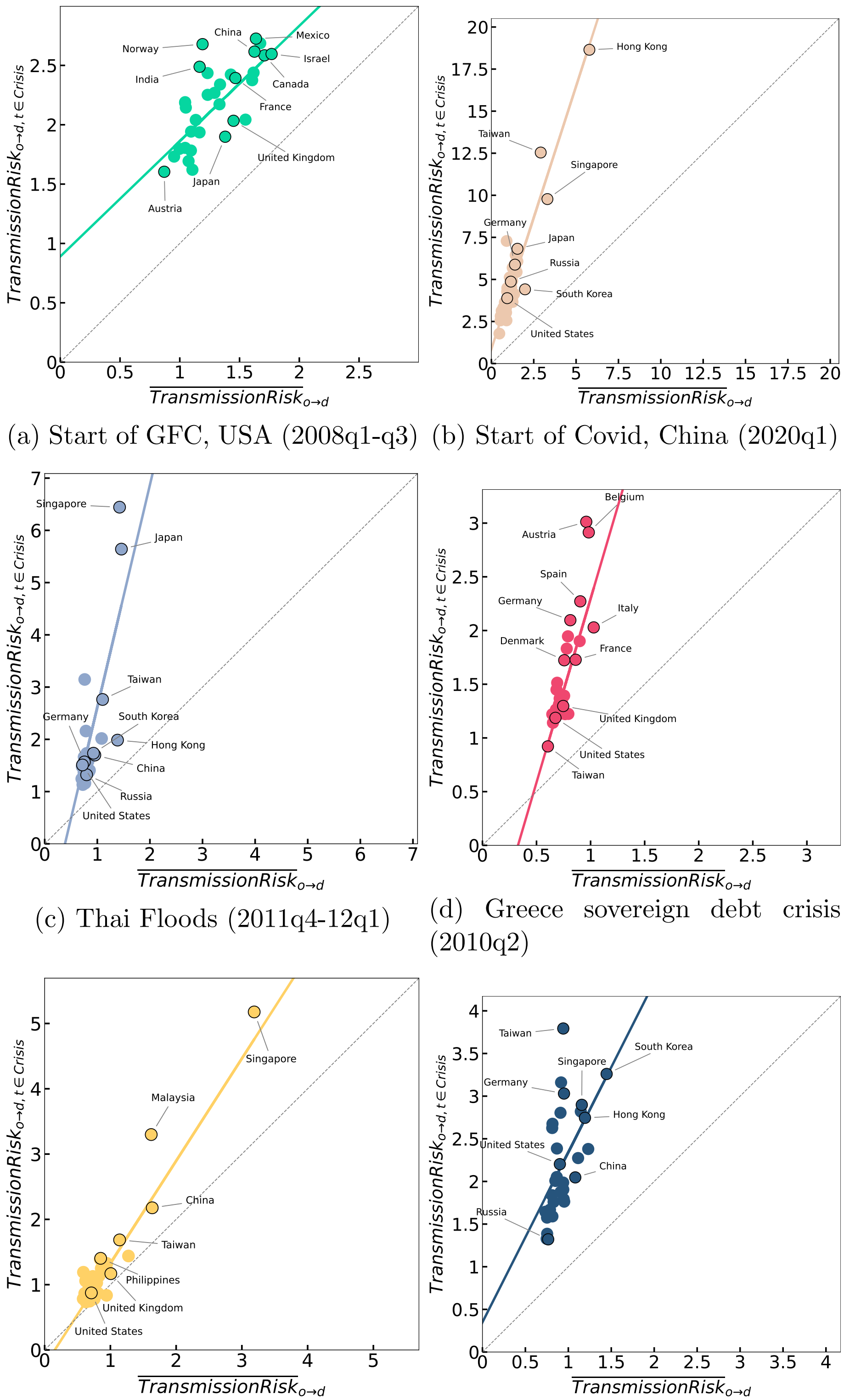
Figure 5: Time series of United States' Country Risk



Summary	Example text excerpts from high-impact snippets
Iraq war (2003q1)	"[...] the US and other parts of the world and related US military action overseas For further descriptions of these risks and uncertainties [...]" (Charles River Laboratories International Inc, February 4, 2003) "[...] 'experiencing in the capital markets the slower recovery in the US and the geopolitical uncertainty Turning to slide three youll see we [...]" (Bank of Montreal, February 25, 2003)
GFC (2008q1 onwards)	"[...] tightening of global credit markets The economic uncertainties in the US and the volatility in equity markets that has resulted from those [...]" (Canaccord Genuity Group Inc, February 7, 2008) "[...] uncertainties in growing economies including high oil prices inflation and US subprime financial crisis We may expect continued paucity of the market [...] (Samsung Electronics Co Lt, April 24, 2008)
S&P downgrade (2011q3)	"[...] recovering with uncertainty and instability Especially recently Standard Poors ((downgraded)) US credit rating from AAA to AA which resulted in stock market [...]" (PetroChina Co Ltd, August 25, 2011) "[...] macro uncertainty and particularly the fiscal uncertainty here in the US I was hoping you could comment on how if at all [...]" (Calamos Asset Management Inc, August 2, 2011)
Fiscal cliff (2012q4)	"[...]the US fiscal cliff and all the macros in the US coupled with EU uncertainty and coupled with maybe some growth uncertainty [...]" (Jefferies Group LLC, Dec. 18, 2012) "[...] fiscal cliff the challenges in the Eurozone the uncertainty of US tax policy and the unknown impact of the US elections all [...]" (Equity One Inc, Nov. 2, 2012)
Trump elected (2016q4)	"[...] the regulatory uncertainty around Affordable Care Act linked to the US election cycle as well as certain uncertainties around MA and enrollment [...]" (Syntel Inc, October 20, 2016) "[...] the overall state of the economic climate primarily in the US and the possibility of changing international trade policies worldwide Thank you [...]" (Collectors Universe Inc, February 2, 2017

Notes: This figure plots the time series of United States $CountryRisk_{c,t}$ as defined in equation (2), 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 30 highest-ranked firms when sorted on Country Risk for the United States.

Figure 6: Crisis Transmission



(a) Start of GFC, USA (2008q1-q3)

(b) Start of Covid, China (2020q1)

(c) Thai Floods (2011q4-12q1)

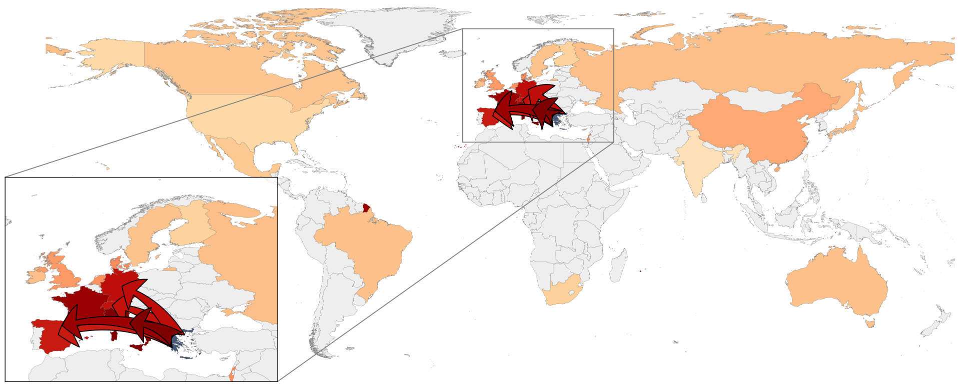
(d) Greece sovereign debt crisis (2010q2)

(e) Regular: Hong Kong protests (2019q3-2020q1), $R^2 = 0.95$

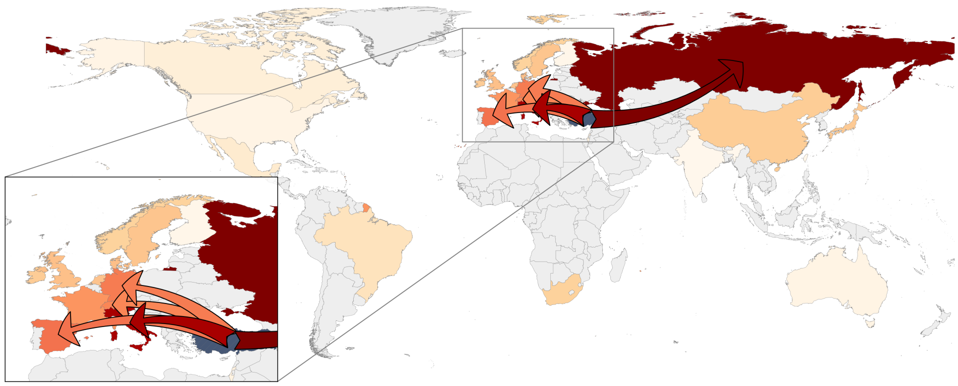
(f) Irregular: Fukushima (2011q2), $R^2 = 0.32$

Notes:

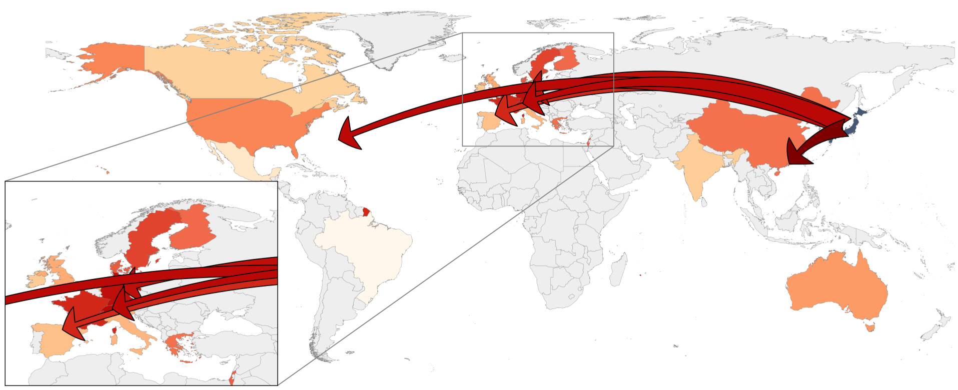
Figure 7: Country Risk transmitted through firm exposures: Three examples



(a) Greek crisis (2010-2012)



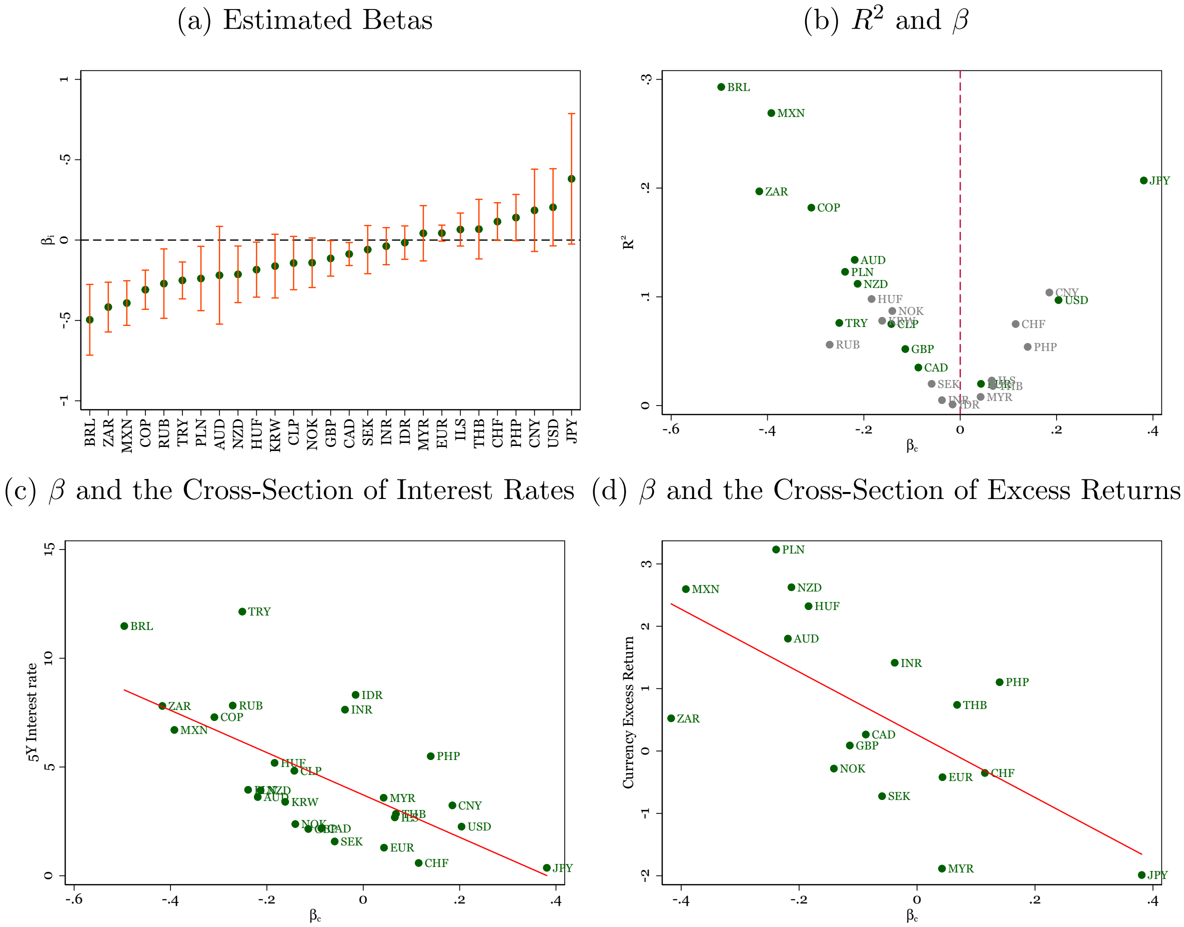
(b) Turkish coup (2016)



(c) Fukushima disaster (2011)

Notes: This figure plots the countries in which firms have the highest average $TransmissionRisk_{i,t}$ during the following three crisis episodes selected from Table 2: the Greek crisis in 2010-2012, the Turkish coup in 2016, and the Fukushima disaster in 2011. We also plot arrows to the top 5 countries with firms that have the highest average $TransmissionRisk_{i,t}$. For the Greek crisis, these are Italy, France, Germany, Switzerland, and Spain; for the Turkish coup, these are Russia, Italy, Spain, Germany, and Switzerland; and for the Fukushima disaster these are Hong Kong, Switzerland, Bermuda, Germany, and France. Darker colors indicate higher $TransmissionRisk_{i,t}$. Countries in grey indicate that we do not have > 25 firms headquartered in that country during the episode.

Figure 8: Exchange Rates and Global Risk: Equal-Weighted Broad Exchange Rate



Notes: This figure plots the coefficient β_i for regressions of the form

$$\Delta e_{i,t}^{B} = \alpha_i + \beta_i \Delta \log GlobalRisk_t + \epsilon_{i,t}$$

against a number of variables. Panel (a) reports the point estimates and two standard error bands. Panel (b) plots the point estimates of β_i on the x-axis and the R^2 of the regression on the y-axis . The dashed vertical line denotes $\beta_i = 0$. If a marker is in gray, it indicates that on average over the sample period, the exchange rate was less flexible than a "managed float" in the Ilzetzki et al. (2019) classification. Panel (c) plots the β_i against the average 5-year government nominal interest rates from Du et al. (2018). Panel (d) plots the β_i against the average excess return against the USD from Hassan and Zhang (2020).

Appendix Table 1: Number of firms linked to countries

Country	HQ	Sales	Subsidiaries	Subsidiaries (updated)
United States	6,623	1,319	7,427	7,011
Canada	918	886	3,786	3,759
United Kingdom	548	990	4,351	4,265
Australia	434	385	2,392	2,461
India	362	193	1,992	2,099
China	349	738	2,614	2,675
Japan	230	595	1,879	1,958
Germany	219	698	2,979	3,019
Sweden	198	118	1,605	1,656
Brazil	178	272	2,009	2,272
France	161	405	2,689	2,664
Switzerland	125	145	0	1,968
Hong Kong	115	113	2,251	2,354
Israel	114	74	832	946
Italy	109	247	1,988	2,042
Netherlands	104	207	2,903	2,922
Mexico	98	308	1,916	1,988
Norway	96	102	1,162	1,237
South Africa	96	96	1,182	1,243
Spain	75	199	2,114	2,169
Ireland	73	90	1,812	1,888
New Zealand	62	85	1,040	1,156
Singapore	56	208	2,195	2,401
Russia	54	101		
Taiwan	49	179		
Belgium	45	120		
South Korea	45	233		
Greece	41	27		
Poland	32	86		
Chile	31	88		
Turkey	27	61		
Thailand	24	74		
Malaysia	23	112		
Argentina	20	94		
Philippines	20	61		
Indonesia	18	66		
Colombia	16	67		
Nigeria	14	29		
Egypt	8	28		
Czech Republic	6	57		
Hungary	4	40		
Pakistan	4	8		
Saudi Arabia	3	31		
Venezuela	2	36		
Iran	0	0		

Notes: This table shows for the 45 countries for which we have text-based measures of country exposure, risk and sentiment and the number of firms that are headquartered in the country (column 1) or report part of their sales to the country (column 2). The headquarter of a firm is from Compustat and based on the `loc` variable and sales are from the Worldscope segment data.

Appendix Table 2: Top 100 risk synonyms

Synonym	Frequency	Synonym	Frequency
risk	3,839,353	skepticism	8,674
risks	1,033,976	unresolved	8,461
uncertainty	921,751	jeopardy	6,761
variable	816,649	risking	6,414
uncertainties	549,476	suspicion	6,359
possibility	484,545	hesitating	4,354
pending	426,103	halting	4,334
uncertain	382,217	peril	4,259
chance	360,536	risked	4,126
doubt	285,218	unreliable	3,971
prospect	211,168	insecurity	3,105
exposed	176,667	undetermined	3,092
variability	175,526	apprehension	2,881
likelihood	159,348	undecided	2,715
threat	133,385	wager	2,678
probability	132,931	precarious	2,577
bet	110,781	torn	2,563
varying	85,282	unsafe	2,470
unknown	83,956	unforeseeable	2,305
unclear	75,460	debatable	2,178
doubtful	74,169	wavering	1,798
unpredictable	67,065	riskiest	1,788
speculative	58,116	dicey	1,764
fear	51,378	endanger	1,547
hesitant	47,043	faltering	1,530
reservation	47,003	changeable	1,527
risky	44,332	indecision	1,505
sticky	39,321	hazy	1,476
instability	36,955	iffy	1,269
tricky	33,849	ambivalent	1,255
dangerous	26,551	riskiness	1,248
tentative	26,126	insecure	1,189
fluctuating	26,070	oscillating	1,075
gamble	22,149	quandary	1,022
hazardous	21,836	dubious	957
hazard	21,580	hairy	884
queries	20,899	treacherous	753
danger	18,695	unreliability	626
unstable	18,396	perilous	565
erratic	14,325	tentativeness	479
vague	14,030	chancy	461
unpredictability	13,853	wariness	439
query	13,559	vagueness	375
unsettled	12,563	dodgy	318
jeopardize	12,528	indecisive	262
riskier	11,650	menace	239
irregular	10,161	equivocation	224
dilemma	9,660	vacillating	198
hesitancy	9,342	imperil	191
unsure	8,715	vacillation	159

Notes: This table lists the top 100 synonyms of risk, risky, uncertain, and uncertainty sorted by their frequency in the earnings call transcripts in 2002-2019. The synonyms are taken from the Oxford Dictionary.

Appendix Table 3: Top 100 positive and negative sentiment words

Positive	Frequency	Positive	Frequency	Negative	Frequency	Negative	Frequency
strong	17,221,419	enable	886,239	loss	6,235,657	discontinued	487,232
good	16,375,745	encouraged	884,693	decline	6,154,079	unfavorable	479,038
better	7,991,201	achieving	796,439	negative	3,647,119	unfortunately	453,610
positive	7,751,315	strengthen	784,057	restructuring	2,684,909	volatile	453,414
opportunities	7,192,361	tremendous	779,182	against	2,659,956	nonperforming	437,280
able	6,702,060	exciting	744,928	difficult	2,659,392	adverse	429,524
improvement	6,673,141	strengthening	715,638	losses	2,556,652	closure	411,024
great	6,563,803	enhanced	708,264	declined	2,545,940	recession	395,192
improved	5,348,573	innovative	699,642	closed	1,726,966	disclose	378,916
progress	5,029,603	encouraging	688,923	late	1,709,514	slowing	378,514
opportunity	4,914,614	gaining	575,582	challenging	1,584,998	missed	370,918
benefit	4,543,771	easy	570,340	challenges	1,574,903	slowed	368,101
improve	4,378,622	stability	541,004	closing	1,507,678	lag	357,819
pleased	3,884,671	exceptional	528,189	force	1,318,218	termination	352,703
profitability	3,607,335	strongest	511,179	critical	1,170,235	bridge	351,936
best	3,544,899	collaboration	504,330	volatility	1,158,349	disruption	343,899
despite	2,824,225	positively	480,821	declines	1,061,590	worse	340,022
improving	2,764,809	impressive	455,572	weak	1,052,269	lose	333,493
effective	2,744,475	easier	453,072	impairment	1,034,395	severe	332,344
strength	2,675,074	enabled	440,147	slow	1,010,332	stress	325,392
success	2,638,992	excellence	431,839	recall	947,283	downward	322,255
gain	2,598,697	progressing	430,567	concerned	946,866	deterioration	317,373
gains	2,569,678	strengthened	422,980	bad	907,228	chargeoffs	298,441
greater	2,481,712	benefiting	412,070	claims	900,164	doubt	285,218
stable	2,436,356	superior	409,739	break	873,699	unemployment	283,048
improvements	2,424,249	gained	409,422	lost	821,492	shut	282,167
successful	2,410,367	winning	394,088	weakness	806,320	drag	281,006
achieved	2,372,811	exclusive	388,657	negatively	803,988	losing	280,300
achieve	2,357,358	enhancing	376,798	problem	786,382	wrong	274,826
confident	2,328,839	advantages	373,082	challenge	773,386	closures	265,476
efficiency	2,208,954	perfect	357,260	weaker	764,882	opportunistic	254,129
favorable	2,026,078	efficiently	351,828	slowdown	738,435	difficulties	249,851
stronger	2,016,286	stabilized	351,444	difficulty	738,121	slowly	248,400
leading	1,984,440	enables	350,678	slower	735,585	impairments	247,091
advantage	1,842,244	satisfaction	350,091	cut	734,201	challenged	238,877
profitable	1,702,117	valuable	349,853	declining	730,136	poor	235,879
attractive	1,556,455	enabling	336,446	litigation	685,502	absence	235,696
innovation	1,391,174	alliance	316,024	crisis	680,481	serious	230,349
leadership	1,387,836	stabilize	313,098	problems	616,975	shutdown	225,476
excited	1,374,945	rebound	307,477	delay	570,659	complicated	224,854
excellent	1,299,652	easily	287,979	downturn	563,302	bankruptcy	220,373
happy	1,258,276	favorably	280,433	opposed	563,195	divestiture	215,695
optimistic	1,215,776	enjoy	278,973	delays	562,781	attrition	215,068
highest	1,128,349	boost	268,376	dropped	549,988	shortfall	214,061
efficiencies	1,087,947	satisfied	266,476	disclosed	535,594	weakening	213,005
efficient	1,086,825	enhancements	264,166	concern	522,931	disappointing	211,210
enhance	1,078,709	achievement	261,148	lack	515,471	erosion	210,240
successfully	1,048,883	improves	259,611	breakdown	510,491	caution	208,764
benefited	928,965	accomplished	258,083	delayed	508,852	broken	206,668
win	904,122	strengths	252,403	concerns	489,061	writeoff	203,273

Notes: This table lists the top 100 positive (columns 1-4) and negative (columns 5-8) tone words sorted by their frequency in the earnings call transcripts in 2002-2019. The tone words are from Loughran and McDonald (2011).

Appendix Table 4: Comparison with WUI and EPU

	Total inflows$_{c,t}$ (%)				
	(1)	(2)	(3)	(4)	(5)
CountryRisk$_{c,t}$ (std.)	–0.700***		–0.672***		–0.568***
	(0.159)		(0.159)		(0.166)
World uncertainty index$_{c,t}$ (std.)		–0.118**	–0.083		
		(0.057)	(0.054)		
EPU national$_{c,t}$ (std.)				–0.192*	–0.082
				(0.093)	(0.108)
R^2	0.251	0.241	0.252	0.370	0.382
N	2,792	2,792	2,792	1,455	1,455
	Δ CDS spread$_{c,t}$				
	(1)	(2)	(3)	(4)	(5)
Δ log(*CountryRisk$_{c,t}$ (std.)*)	2.418***		2.411***		2.484**
	(0.789)		(0.855)		(1.125)
Δ log(*World uncertainty index$_{c,t}$ (std.)*)		0.055*	0.053*		
		(0.033)	(0.032)		
Δ log(*EPU national$_{c,t}$ (std.)*)				0.135	0.113
				(0.108)	(0.105)
R^2	0.165	0.149	0.168	0.162	0.187
N	2,626	1,866	1,866	1,378	1,378
Country FE	yes	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes	yes

	log(investment rate$_{i,t}$)				
	(1)	(2)	(3)	(4)	(5)
CountryRisk$^{NHQ}_{c(i),t}$ (std.)	–0.201***		–0.198***		–0.164***
	(0.022)		(0.022)		(0.024)
World uncertainty index$_{c,t}$ (std.)		–0.022***	–0.004		
		(0.005)	(0.005)		
EPU national$_{c,t}$ (std.)				–0.071***	–0.039***
				(0.010)	(0.010)
R^2	0.512	0.511	0.512	0.510	0.511
N	71,673	72,927	71,673	67,467	67,467
	Δ log(employment$_{i,t}$)				
	(1)	(2)	(3)	(4)	(5)
CountryRisk$^{NHQ}_{c(i),t}$ (std.)	–0.031***		–0.034***		–0.033***
	(0.005)		(0.005)		(0.006)
World uncertainty index$_{c,t}$ (std.)		–0.000	0.003**		
		(0.001)	(0.001)		
EPU national$_{c,t}$ (std.)				–0.005**	0.001
				(0.002)	(0.002)
R^2	0.233	0.232	0.233	0.232	0.232
N	67,266	68,534	67,266	63,536	63,536
Firm FE	yes	yes	yes	yes	yes
Year-quarter FE	yes	yes	yes	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level (Panels A and B) and at the firm-year level (Panels C and D). Standard errors are clustered at the country level in Panels A and B and at the firm level in Panels C and D.

Appendix Table 5: $\mathit{TransmissionRisk}_{c(i),c}$ follows a gravity structure

	$\overline{\mathit{TransmissionRisk}}_{o \to d}$		
	(1)	(2)	(3)
Log of distance (km)$_{o,d}$		–0.393***	–0.294***
		(0.042)	(0.048)
$\mathbb{1}$(Contiguity$_{o,d}$)		0.591**	0.522**
		(0.248)	(0.232)
$\mathbb{1}$(Common language$_{o,d}$)		0.585***	0.437***
		(0.137)	(0.104)
$\mathbb{1}$(Ever in colonial relationship$_{o,d}$)		0.158	0.185
		(0.149)	(0.154)
$\mathbb{1}$(Log of trade flows in 2019$_{o,d}$)			0.136***
			(0.022)
R^2	0.160	0.347	0.395
N	1,988	1,984	1,760
Origin FE	yes	yes	yes
Destination FE	yes	yes	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-country level. Similar to Table 9, $\mathit{TransmissionRisk}_{c(i),c}$ is defined as the sum over the relevant components of $\mathit{ForeignRisk}_{i,t} := \sum_{c \neq c(i)} \mathit{CountryExposure}_{i,c,t} \times \widetilde{\mathit{CountryRisk}}_{c,t}$ for country-country pairs. For example, for country-country pair $(c(i), c)$, we take the sum over all firms headquartered in country $c(i)$ of the relevant components about country c: $\sum_{i \in c(i), c=c} \mathit{CountryExposure}_{i,c,t} \times \widetilde{\mathit{CountryRisk}}_{c,t}$. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 6: Correlation with sudden stops and rentrenchment episodes (Forbes & Warnock)

	All countries		Emerging markets		Developed	
PANEL A: SUDDEN STOPS	$\mathbb{1}(\textit{Stop episode for total flows}_{c,t})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$CountryRisk^{ALL}_{c,t}$ *(std.)*	0.082**	0.086**	0.112**	0.112**	0.032	0.021
	(0.037)	(0.033)	(0.053)	(0.045)	(0.042)	(0.031)
$GlobalRisk_t$ *(std.)*	0.005***		0.004***		0.005***	
	(0.001)		(0.001)		(0.001)	
R^2	0.095	0.338	0.108	0.290	0.085	0.477
N	2,734	2,734	1,396	1,396	1,338	1,338
PANEL B: RENTRENCHMENT	$\mathbb{1}(\textit{Retrenchment episode for total flows}_{c,t})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$CountryRisk^{ALL}_{c,t}$ *(std.)*	0.009	0.011	–0.002	0.003	0.024	0.014
	(0.025)	(0.020)	(0.026)	(0.026)	(0.047)	(0.031)
$GlobalRisk_t$ *(std.)*	0.004***		0.004***		0.005***	
	(0.001)		(0.001)		(0.002)	
R^2	0.053	0.260	0.039	0.166	0.063	0.420
N	2,734	2,734	1,396	1,396	1,338	1,338
Country FE	yes	yes	yes	yes	yes	yes
Year-quarter FE	no	yes	no	yes	no	yes

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quarter level. All variables are defined as in Table 3. Standard errors are clustered at the country level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 7: When things go haywire, capital flows to the US

	Total inflows$_{c,t}$ (%)			*Portfolio inflows$_{c,t}$ (%)*
	(1)	(2)	(3)	(4)
CountryRisk$_{c,t}$ (std.)	–0.735***	–0.782***	–0.715***	–1.063*
	(0.182)	(0.170)	(0.164)	(0.530)
$US_c \times CountryRisk_{c=US,t}$ (std.)		0.651***	0.211	0.910**
		(0.130)	(0.141)	(0.402)
GlobalRisk$_t$ (std.)	–0.244**	–0.239**		
	(0.112)	(0.110)		
Real GDP growth$_{c,t}$	–0.008	–0.008		
	(0.008)	(0.008)		
R^2	0.125	0.126	0.251	0.131
N	2,657	2,657	2,792	2,936
	Total inflows$_{c,t}$ (%)			*Portfolio inflows$_{c,t}$ (%)*
	(1)	(2)	(3)	(4)
CountryRisk$_{c,t}$ (std.)	–0.735***	–0.777***	–0.727***	–1.079**
	(0.182)	(0.178)	(0.163)	(0.526)
$JP_c \times CountryRisk_{c=JP,t}$ (std.)		0.673***	0.445**	1.352**
		(0.136)	(0.165)	(0.517)
GlobalRisk$_t$ (std.)	–0.244**	–0.237**		
	(0.112)	(0.111)		
Real GDP growth$_{c,t}$	–0.008	–0.008		
	(0.008)	(0.008)		
R^2	0.125	0.126	0.251	0.131
N	2,657	2,657	2,792	2,936
	Total inflows$_{c,t}$ (%)			*Portfolio inflows$_{c,t}$ (%)*
	(1)	(2)	(3)	(4)
CountryRisk$_{c,t}$ (std.)	–0.735***	–0.669***	–0.632***	–0.928*
	(0.182)	(0.179)	(0.152)	(0.475)
$EZ_c \times CountryRisk_{c=EZ,t}$ (std.)		–1.284***	–1.325***	–1.365
		(0.306)	(0.313)	(0.875)
GlobalRisk$_t$ (std.)	–0.244**	–0.163		
	(0.112)	(0.118)		
Real GDP growth$_{c,t}$	–0.008	–0.008		
	(0.008)	(0.008)		
R^2	0.125	0.134	0.260	0.132
N	2,657	2,657	2,792	2,936
Year-quarter FE	no	no	yes	yes
Country FE	yes	yes	yes	yes

Notes:

Appendix Table 8: Comparing different versions of $CountryRisk_{c,t}$

Panel A: Total inflows	Unweighted			Weighted by	
	All firms	Large firms	Small firms	Log of assets	Box-Cox transformed assets
	Total inflows$_{c,t}$ (%)				
	(1)	(2)	(3)	(4)	(5)
$CountryRisk^{ALL}_{c,t}$ *(std.)*	–0.700***	–0.535***	–0.482***	–0.681***	–0.657***
	(0.159)	(0.133)	(0.159)	(0.151)	(0.143)
R^2	0.251	0.253	0.243	0.252	0.253
N	2,792	2,792	2,792	2,792	2,792
Year-quarter FE	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes

Panel B: Within-country correlations	Unweighted			Weighted by	
	All firms	Large firms	Small firms	Log of assets	Box-Cox transformed assets
All firms	1.000				
Large firms	0.945	1.000			
Small firms	0.844	0.623	1.000		
Log of assets	0.992	0.950	0.816	1.000	
Box-Cox transformed assets	0.983	0.964	0.772	0.997	1.000

Notes: This table shows coefficient estimates and standard errors from regressions at the country-quater level. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

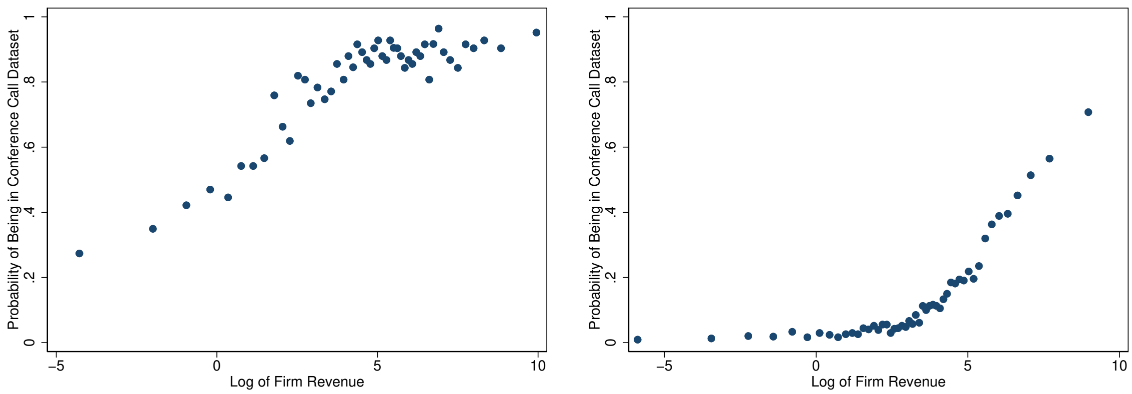
Appendix Table 9: Timing of capital flows

	Total inflows$_{c,t}$ *(%)*			*Portfolio*$_{c,t}$ *(%)*		
	(1)	(2)	(3)	(4)	(5)	(6)
$CountryRisk^{ALL}_{c,t}$ *(std.)*	–0.700***			–0.999*		
	(0.159)			(0.512)		
$\Delta CountryRisk^{ALL}_{c,t}$ *(std.)*		–0.324**	–0.319*		–0.535*	–0.404
		(0.146)	(0.181)		(0.311)	(0.481)
$\Delta CountryRisk^{ALL}_{c,t-1}$ *(std.)*			0.004			–0.093
			(0.114)			(0.201)
R^2	0.251	0.245	0.248	0.130	0.128	0.128
N	2,792	2,757	2,722	2,936	2,899	2,862
Year-quarter FE	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes

Notes:

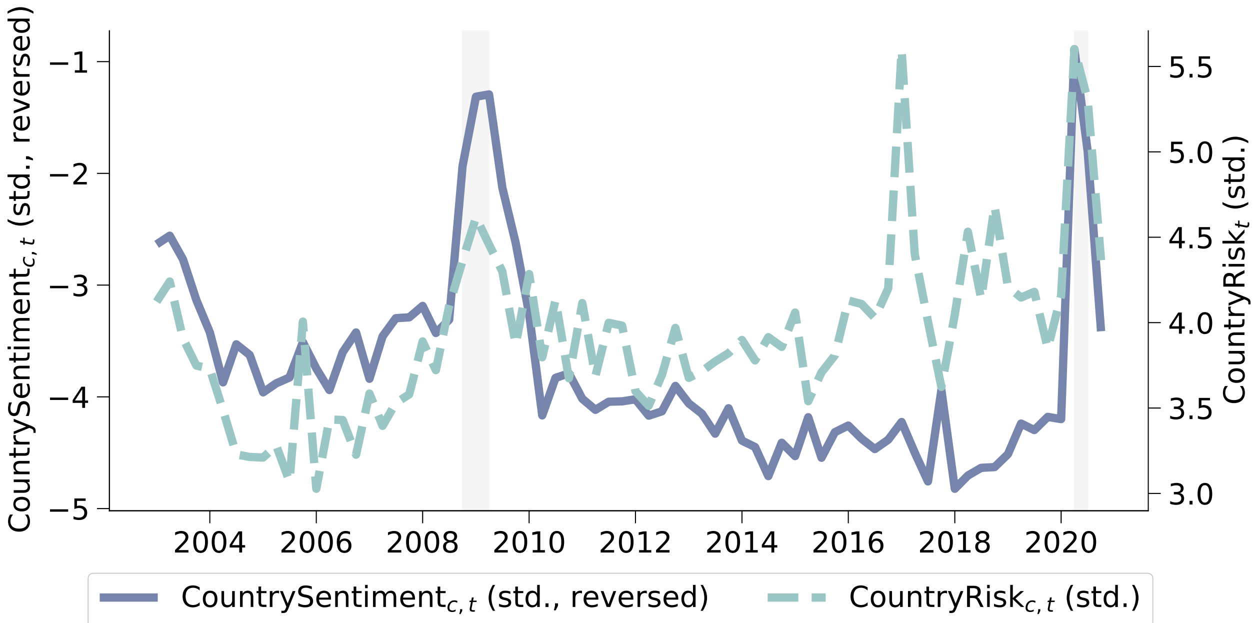
Appendix Figure 1: Firms appearing in Conference Call Dataset, 2018Q4

(a) United States (b) All Other Countries



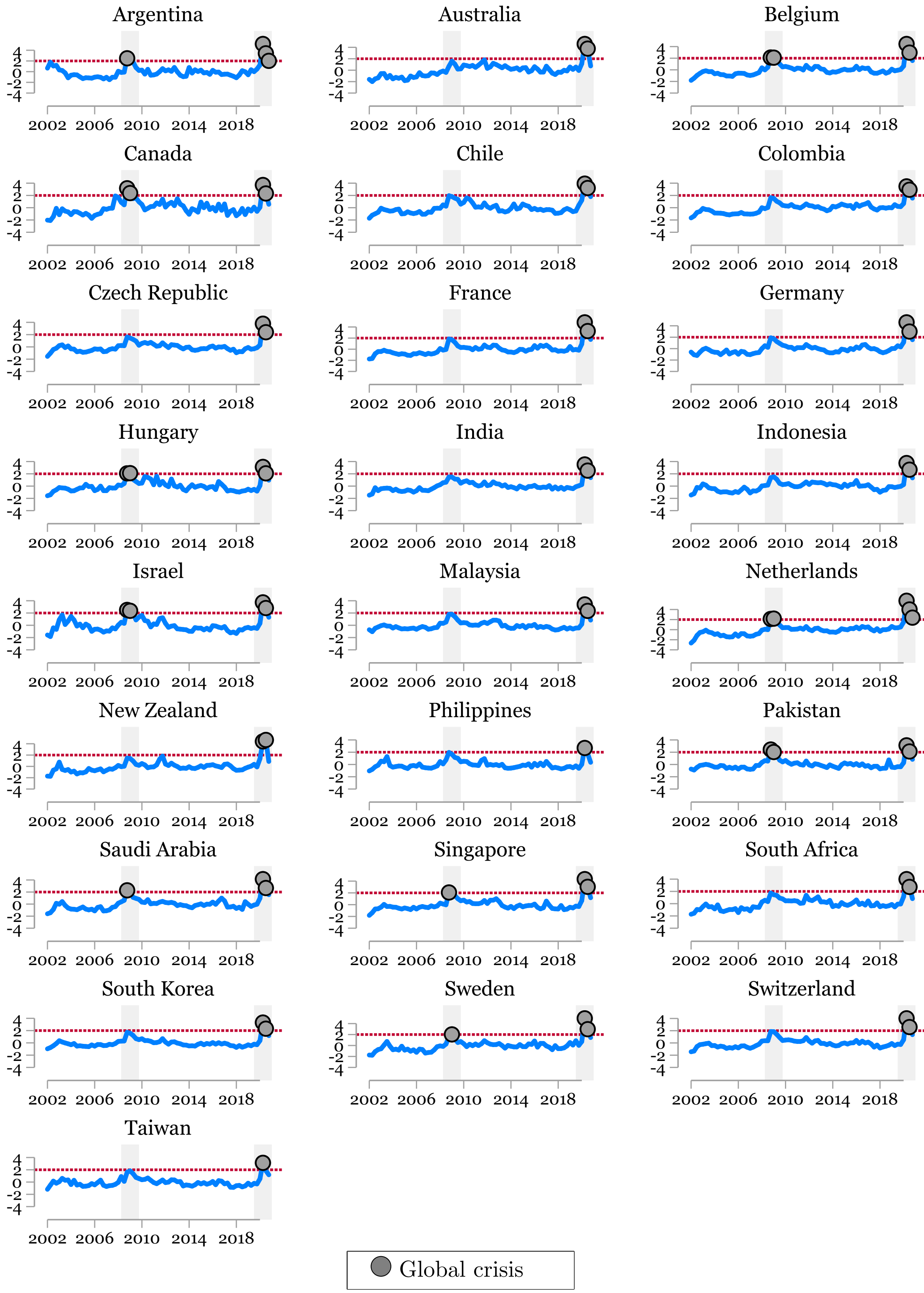
Notes: This figure is a binscatter of a dummy for appearing in the EIKON dataset of conference calls for all firms in Compustat Global in the fourth quarter of 2018.

Appendix Figure 2: Time series of Mexican $CountryRisk_{c,t}$ and $CountrySentiment_{c,t}$

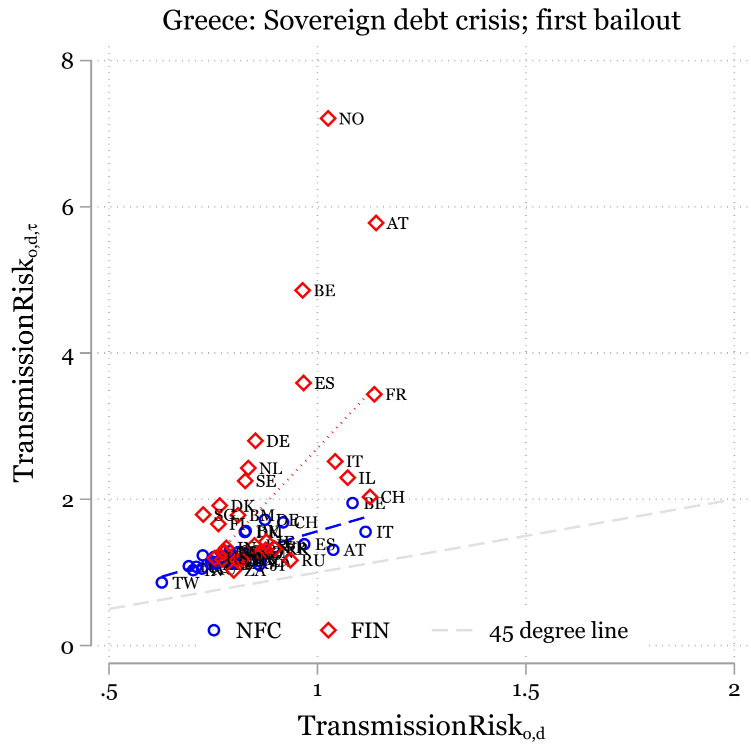


Notes: This figure shows the time series of $CountrySentiment_{c,t}$ *(std.)* and $CountryRisk_{c,t}$ *(std.)*. The time series for $CountrySentiment_{c,t}$ is reversed (multiplied by −1) to facilitate a direct comparison with $CountryRisk_{c,t}$. The coefficients are standardized to have mean zero and standard deviation one for 2002q1-2019q4. NBER-based recession quarters are shaded in grey.

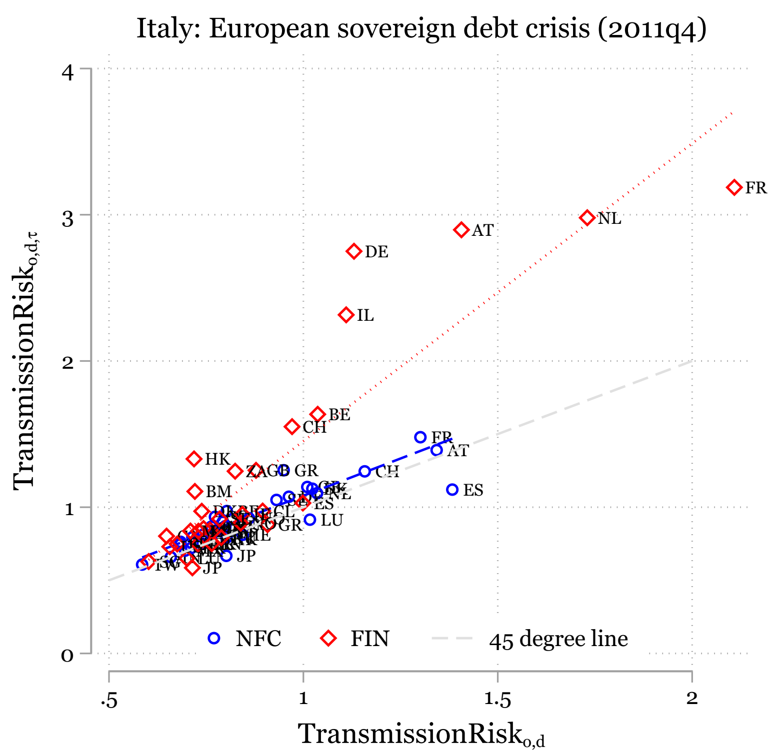
Appendix Figure 3: Countries with no local crises



Notes: This table shows the time series of $CountryRisk_{c,t}$ for all countries that do not have local crises as defined in Figure 2.

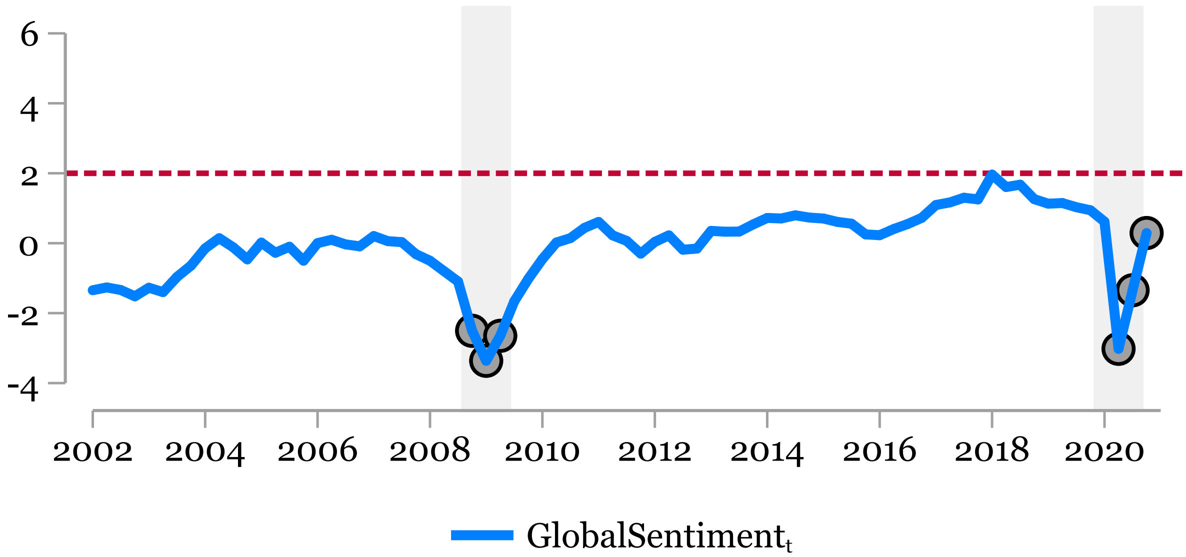


(a) Option # 1



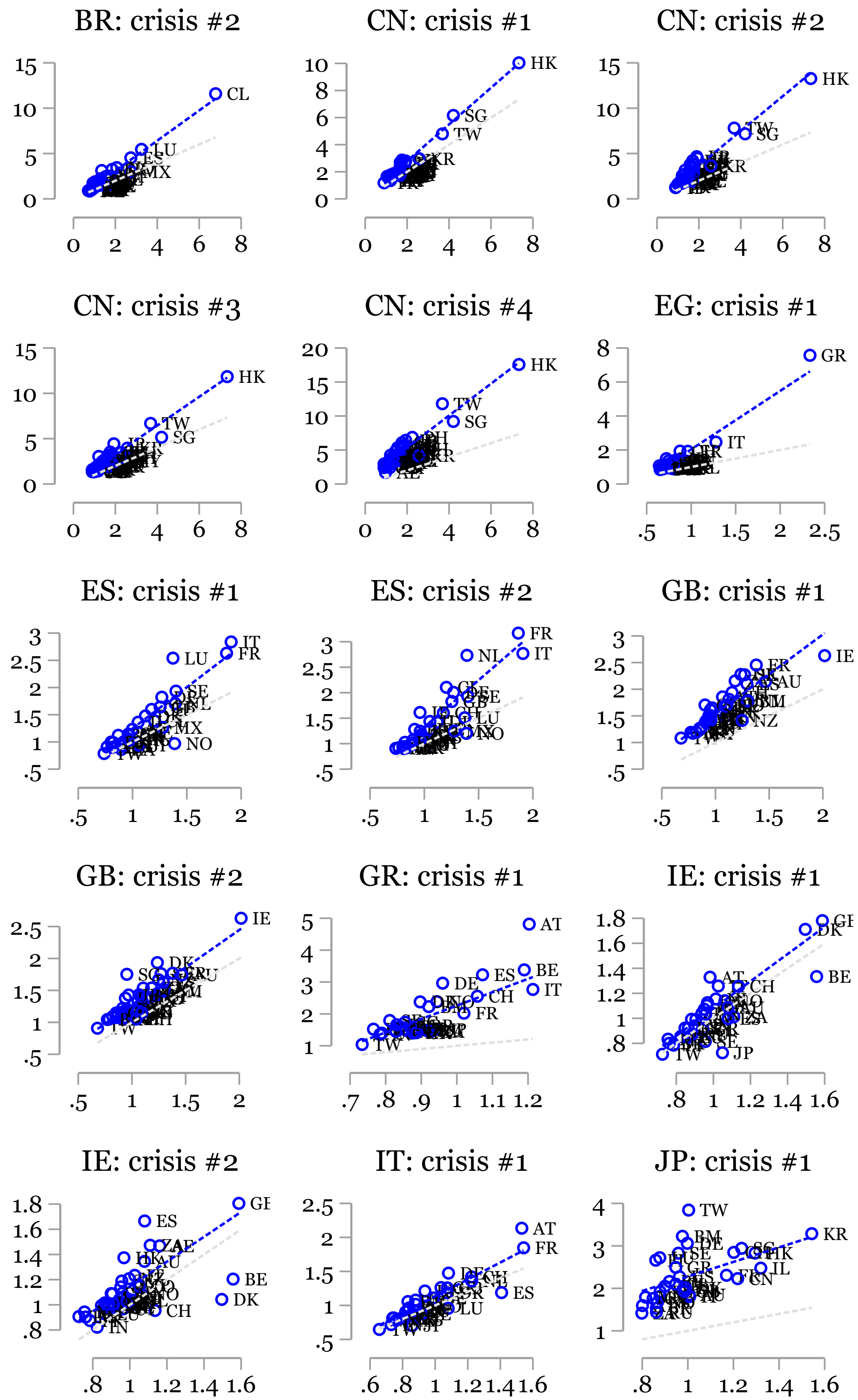
(b) Option #2

Appendix Figure 5: Time series of $GlobalSentiment_t$



Notes: This figure shows the time series of $GlobalSentiment_t$ defined as the mean of $CountrySentiment_{c,t}$. Marked in gray 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.

Appendix Figure 6: $TransmissionRiskCrisis_{o \to d}$ versus $TransmissionRiskNormal_{o \to d}$



Appendix Figure 6: $TransmissionRiskCrisis_{o \to d}$ versus $TransmissionRiskNormal_{o \to d}$ (continued)