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Systemic political risk

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A B S T R A C T

Political risk impacts firm-level risk, influencing funding costs, cash holdings, and capital structure choices. Traditional approaches to political risk rely on aggregate indicators, like economic policy uncertainty proxies. In contrast, our study examines how political risk spreads among individual US firms and sectors using network analysis and systemic risk indicators. This approach identifies crucial and vulnerable actors, not possible with aggregate proxies. We demonstrate the spread of political risk among firms and establish the utility of monitoring neighboring firms to predict potential political risk for a specific firm. Thus, firm-level political risk is not just an idiosyncratic concern but also a systemic one. Additionally, we find that the most central political risk actors are the most sensitive to economic cycles.

1. Introduction

Organization and management studies have traditionally associated political risk with the strategic management considerations of multinational enterprises, frequently within the context of investment decisions that involve the firm's presence in emerging countries sensitive to political turmoil (e.g. Holburn and Zelner, 2010; Stevens et al., 2016; Dai et al., 2017; King et al., 2021; Cannizzaro, 2020). However, recent historical events, ranging from epidemiological threats, wars and economic sanctions to the unexpected (and often unintended) economic outcomes of a polarized political mood (e.g. Brexit), have made it evident that political risk is a determinant of business continuity even in the most developed markets (see, for instance, Hassan et al., 2019; Hasija et al., 2020) and this is recognized as such by corporate executives, who rank political risk as more important than traditional risks, such as commodity (input) risk (Giambona et al., 2017).

According to Hassan et al. (2019), political risk can be defined as the risk arising from the political system that impacts investment, employment, and various aspects of firm behavior. The authors propose a method to measure political risk at the individual firm level by applying text analysis to quarterly earnings conference call transcripts. This approach provides an indicator of the exposure to political risk for listed companies in the US and its variation over time. In contrast to traditional approaches, such as those recently analyzed for instance by Kumar et al. (2021) and Kim et al. (2021), which rely on aggregate indicators like economic policy uncertainty proxies (e.g. Baker et al., 2016) or market volatilities, assessing political risk directly at the individual level offers several advantages.

One significant advantage is the ability to define and estimate a political risk network, which shows how political risk spreads among firms. This approach also enables the identification of sector clusters and key actors at the individual level, which is not possible with aggregate political risk proxies. In other words, network analysis allows for an endogenous modeling of the systemic nature of political risk, rather than condensing it into a single indicator where individual components cannot be distinguished. Indeed, it is challenging to isolate political risk at the aggregate level from other non-political forms of risk that affect firms' operation.

We are the first to estimate the network of political risk using the individual-level political risk measures provided by Hassan et al. (2019).

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Our analysis demonstrates that even if more of the variation in individual political risk is due to idiosyncratic political risk as shown by Hassan et al. (2019), and important component of such risk is systematic (in the sense that it affects a large share of firms which are connected in the network). This means that political risk spreads across firms in a way that allows us to predict (in a Granger sense) an increase in political risk for a specific firm after observing an increment in political risk for other neighboring firms. Therefore, political risk at the firm level is not solely an idiosyncratic concern but also a systemic one. Additionally, we can identify major players in the political risk network, who contribute to the general spread of political risk, as well as other actors that are particularly sensitive to political risk within the system, all of which is novel for the literature.

Various studies have shown that political risk is, indeed, an important source of firm-level risk, which has an impact, among other things, on funding costs, cash holdings, capital structure choices made by corporations, corporate social responsibility and corporate green innovation (Huang et al., 2015; Duong et al., 2020; Lee et al., 2021; Yuan et al., 2022; Cui et al., 2023; Cao et al., 2022). Yet, this literature is silent on how political risk spreads; indeed, it has yet to raise the question as to whether this risk even spreads at all. This comes as a surprise, as political risk is likely to propagate across firms if a political shock to an influential company can be expected to increase political uncertainty in sectors or countries as a whole or if this same political shock can trigger the introduction of new policies that, in turn, may expose a different set of firms, seemingly isolated from the original political shock, to increased political risk. Moreover, under imperfect information, idiosyncratic political shocks could be interpreted by company peers as a sign of a larger shock, which might affect other companies and fuel fear-based contagion. These effects are further amplified by the more subjective nature of political risk compared to its economic counterpart (Bremmer and Zakaria, 2006), and the fact that managerial perceptions of political risk – as opposed to the actual level of risk – are a stronger determinant of how firms behave when having to face such risk (Giambona et al., 2017).

To be able to diversify political risk away, embrace political lobbying or enact measures in the pursuit of firm legitimacy – all in an effort at reducing exposure to political risk (see for instance, Pham, 2019; Stevens et al., 2016; Sidki Darendeli and Hill, 2016; Sun et al., 2015) – managers need to know whether political risk actually propagates, and if it does, how it propagates and how the signs of political risk might be interpreted by different firms within a market economy's political risk network. Here, we seek to fill this gap in the literature and, in so doing, to provide a fresh perspective on the contagious nature of political risk across organizations. For the first time, we study how the idiosyncratic perception of political risk in companies spreads within a large network of firms that can be considered representative of the different sectors that make up the US economy. In this way, we introduce a new research direction in this field, one that considers political risk as both dynamic and systemic as opposed to as an isolated idiosyncratic concern for firms and governments.

We tackle our research question by drawing on a variety of tools and data developed recently in the political and systemic risk literature in the fields of finance and banking. Our point of departure is the systematic account of political risk provided by Hassan et al. (2019), who use computational linguistics (Song and Brook Wu, 2008; Manning et al., 2008) to construct an individual-level measure of political risk faced by US firms. In their baseline calculations (which we adopt herein), they employ a training library of political and non-political texts to identify two-word combinations or *bigrams* frequently used in political discourse. They then count the number of times these bigrams occur in a firm's earnings conference calls (hereinafter, 'earnings calls') with their analysts and other interested parties, in conjunction with synonyms for 'risk' or 'uncertainty'. The total length of these calls normalizes this number and political risk indicators with a quarterly frequency are, thus, obtained.

We next select a subsample of 1099 firms with sufficient time variation to detect pairwise causality (in the Granger sense) between the firms and construct a large network of these firms, in which each company is a node in that network and each edge represents the existence of predictive causality from one company's indicator of political risk to that of another company. This network is characterized by the means of systemic risk, as proposed by Billio et al. (2012), which include the number of connections leaving each firm (outgoing), entering each firm (incoming), and passing through each firm.

Our approach allows us to address the following questions: Who are the most central actors in the US political risk network? Which firms are most vulnerable to political risk shocks from other firms in the network? Which companies generate most political risk shocks with repercussions for the rest of the system? In short, we are able to determine which actors are the most systemically important in the US political risk network. Moreover, in line with previous studies that recognize the heterogeneous nature of the impact of political risk according to a firm's sector (e.g. Stevens et al., 2016; Pham, 2019), we group our estimates in accordance with the eleven industry sectors in the Global Industry Classification Standard (i.e. Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities and Real Estate) and identify patterns of risk propagation across these eleven sectors.

Our results provide clear evidence of the actual propagation of political risk between US firms. That is, of all the possible connections that might have existed between the 1099 firms in our sample – which covers the period from the first quarter of 2006 to the third quarter of 2021 –we identify 89,109 statistically significant connections (7.4% of the total) at the 95% confidence interval. Moreover, we show that our indicators of centrality (i.e. eigenvector centrality and closeness centrality) and systemic importance (i.e. number of outgoing/incoming connections from/to each firm) provide totally novel information about political risk dynamics that is not captured by the original time-average indicators at the firm level used in Hassan et al. (2019). For instance, the correlation between our statistics of centrality and systemic importance, at the firm level, and the average political risk of each firm are very close to zero (between -0.070 and 0.042). Thus, we show that political risk is not necessarily an idiosyncratic concern, but rather that it also presents systemic features of which firms and managers should be aware.

Our results at the firm level indicate that there is heterogeneity in the spectrum of the spread of political risk across US firms, with all eleven sectors represented in the top 25 most central firms in our network (except for communication Services in the case of the closeness centrality measure). However, a number of companies stand out, most notably two operating in the Financials sector, New York Community Bancorp Inc. and American Express Co, being the only two companies in the top 25 firms that not only propagate and receive the most shocks but that also present a high eigenvector centrality indicator. Interestingly, the firms with the highest eigenvector centrality do not tend to overlap with the most frequent propagators of political risk shocks (as well as the two finance firms already mentioned, only TrueBlue Inc. appears in both categories). In contrast, many firms are both central to the network (according to the eigenvalue centrality measure) and vulnerable to shocks. They include DCP Midstream LP (Energy), Interpublic Group (Communication Services), Equity LifeStyle Properties (Real Estate), Universal Electronics and Abercrombie & Fitch Co (both Consumer Discretionary), to cite the most representative examples.

At the sector level, after controlling for the size of each sector, our results identify Consumer Discretionary and Industrials as acting as main givers and receivers of political risk shocks. The Energy sector joins them in this role from 2014 onwards. Other sectors, such as Communication Services frequently receive political risk shocks from the rest of the system but do not amplify them further. Remarkably, Utilities and Health Care are practically isolated from the other sectors from 2014. Finally and most notably, financial firms are not the only (or even the most prominent) source of systemic political risk, as tends to be the case in the systemic risk literature in the field of finance. Overall, these findings highlight the significant role that political risk plays in the larger context of systematic risk in macroeconomics and finance. Sectors that are most sensitive to economic cycles, such as Industrials, Consumer Discretionary, and Energy, are central in the political risk network. As a result, firms in these sectors are particularly aware of the need to diversify their political risk in order to mitigate the potential impact of aggregate consumption risk, which is the cornerstone of intertemporal general equilibrium models and asset pricing studies.

These results invite us to think of political risk – or more precisely, its perception by the boards of directors in different firms – as a source of systemic stress that, ideally, should be monitored by managers and other stakeholders seeking to minimize overall organization risk or to anticipate future concerns that merit the closer examination of policy makers. Given that our results are based on the Granger causality test, they directly reflect the predictive capacity of political risk discourse in conference calls for the future calls of other firms, at least one quarter in advance.

2. Data

The dataset was obtained from https://www.firmlevelrisk.com/download, a website from which it is possible to download measures of exposure, risk and sentiment at the firm-level, constructed using computational textual analysis of the transcripts of the quarterly earning calls of 12,849 firms in 81 countries. The sample period covers the period from the first quarter of 2002 to the third quarter of 2021. The risk indicators use simple computational linguistics tools to quantify the share of earnings calls devoted to discussing risk in general, risks associated with politics, and risks associated with particular political issues, such as health care and economic policy. We employ the political risk indicator proposed by Hassan et al. (2019) and only consider US companies, thus reducing the database to 6867 firms.

Political risk is an indicator of the importance of political issues in a company's quarterly earnings calls. To calculate the measure, a training library of political texts, *P*, and a training library of non-political texts, *N*, are defined. The two libraries consist of all adjacent two-word combinations or bigrams found in the political and non-political texts, respectively. The transcripts of company *i* in quarter *t* are then decomposed into a list of all the bigrams contained in the transcript $b = 1, \ldots, B_{it}$. Finally, the number of occurrences of bigrams referring to political issues that are within 10 words on either side of a synonym for 'risk' or 'uncertainty' are counted and divided by the total number of bigrams in the transcript. Thus, political risk at a quarterly frequency can be calculated using the following formula:

$$Political\ \ risk_{it} = \frac{\sum_{b}^{B_{it}}\left(1[b \in P\backslash N] \times 1[|b-r|<10] \times \frac{f_{b,P}}{B_P}\right)}{B_{it}}$$

where $1[\cdot]$ is the indicator function, $P\backslash N$ is the set of bigrams in *P* but not in *N* and *r* is the position of the nearest risk or uncertainty synonym. The first two terms in the numerator count the number of bigrams associated exclusively with political debate, that occur within 10 words of a synonym for risk or uncertainty. The last term in the numerator reflects how strongly the bigram is related to politics, where $f_{b,P}$ is the number of times bigram b is found in *P*, and B_P is the total number of bigrams in *P*. In the database, the value of political risk obtained is multiplied by 100,000.

In order to work with time series that do not present a large number of missing observations, and taking into account that the missing values are concentrated during the first few years of the sample period, we retained those companies with at least 60 (out of 64) observations available from the last quarter of 2005 to the third quarter of 2021, leaving us with a total of 1099 companies in the database. These companies were grouped by sector using the eleven industry sectors in the Global Industry Classification Standard as outlined above.

Table 1 shows summary statistics of political risk by sector, as well as the number of firms assigned to each sector. Here, we first calculated the average political risk for each company and then calculated the statistics for each sector. The sectors with the highest average political risk are Utilities and Financials, while those with the lowest are Consumer Staples and Consumer Discretionary. In terms of variation, the sectors with the greatest dispersion in their average political risk values are Health Care, Financials and Industrials, while those with the least are Energy, Communication Services and Consumer Discretionary. Moreover, the firms with the highest average political risk values are found in the Industrials and Health Care sectors, while the firms with the lowest values are in the Industrials, Information Technology and Consumer Staples sectors. Finally, the sectors with the highest number of companies among the 1099 companies in the database are Industrials, Consumer Discretionary and Information Technology with 197, 166 and 162 companies, respectively, while the sectors with the fewest are Communication Services and Utilities with 39 and 40 companies, respectively.

3. Methodology

In this section, we explain how our graphs are defined and outline the systemic risk statistics used.

Definition 1. A graph G=(V.A) is a pair formed by two sets. Set V consists of graph vertices or nodes, while set A contains pairs of vertices that are connected and which form the arcs or axes of the graph.

Here, the graph is constructed such that the vertices correspond to the different companies, while the edges are formed by pairs of companies that transmit political risk from one to another. Thus, we obtain a network of companies that are connected to each other by means of the edges. In this study, directed graphs are employed, that is, their arcs are formed by ordered pairs of vertices, each arc having an initial node and a final node which, if inverted, form a different arc. Adjacency matrices are used to represent the graphs (or network).

Definition 2. An adjacency matrix is a square matrix that represents the connections between pairs of vertices. The rows and columns represent the various graph vertices, and the elements of the adjacency matrix indicate which pairs of vertices a given arc connects with. In a directed graph, the elements of a row correspond to the edges leaving a vertex, while the elements of a column correspond to the edges entering the vertex.

Adjacency matrices, representing the political risk transmission between companies, are calculated using Granger causality tests applied to each possible pair (in both possible directions) in the sample.[1]

3.1. Bivariate granger causality tests for network definition

Granger causality is calculated for each pair of firms. That is, political risk is considered to be transmitted from one company to another if the political risk indicator of the first company has predictive power on the second company. In this instance, there would be an arc directed from the node of the first company to that of the second. This calculation is carried out for all ordered pairs of companies in the sample. To decide whether a series X causes, in the Granger sense, series Y, two linear regressions are run and then compared:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_k y_{t-k} + \alpha_1 x_{t-1} + \ldots + \alpha_k x_{t-k} + e_t \qquad (1)$$

[1] We also follow Barigozzi and Brownlees (2019) to estimate the network representation of our system of firms. These authors proposed a LASSO algorithm – or *NETS* (network estimation for time series) – to estimate large sparse VAR models. However, due to the frequency and period span of our data, the *NETS* algorithm only allows us to estimate the network using up to 64 companies. Results are available upon request.

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_k y_{t-k} + e_t \tag{2}$$

where the first forecasting equation uses lags up to order k of the risk indicator of company X and company Y to predict the political risk of company Y, while the second regression explains the risk of company Y using only its own lags. A Wald test with a significance level of 0.01 is then carried out to test the following hypotheses about these two regressions:

$$H_0 : \alpha_i = 0 \; for \; all \; i \in (1, k)$$

$$H_1 : \alpha_i \neq 0 \; for \; some \; i \in (1, k)$$

Therefore, if the null hypothesis is rejected, then the values of series X help to predict future values of series Y, i.e. series X Granger-causes series Y. The number of lags included in Equation (1) is 1. One lag represents a general structure of a Markovian nature in economics, and is the natural choice as a VAR(1) can be used to represent traditional general equilibrium dynamics in macroeconomics. Nevertheless, we test for robustness of our results using four lags (see section 5.1.) Finally, we use the results of the pairwise Granger-causality tests to estimate the network of statistically significant relations among US firms.

3.2. Systemic risk statistics

We next characterize the network using the systemic risk statistics proposed by Billio et al. (2012), which include the number of connections leaving each firm, entering each firm, and passing through each firm. These statistics enable us to identify which firms generate most political risk shocks to the rest of the system, which firms are most vulnerable to political risk shocks from other firms within the network, and which firms play a central role in the US political risk network. To do so, following Billio et al. (2012), we first define an indicator according to the Granger causality test results:

$$(j \rightarrow i) = \begin{cases} 1 \; if \; j \; Granger - causes \; i \\ 0 \; otherwise \end{cases}$$

This indicator function can be used to define the systemic risk statistics that enable us to characterize the network:

- *Degree of Granger causality.* This statistic is calculated as the fraction of significant Granger-causality relationships among the N(N-1) pairs of possible connections:

$$\frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \rightarrow i)$$

The higher the value of the statistic, the deeper the network is and, therefore, the higher the degree of connectedness of the system of firms.

- Number of connections. This statistic gauges the systemic importance of individual firms in the network. Three different counting measures are defined where S is the set of all firms. The first measures the percentage of firms that are Granger-caused by an individual firm *j*, i.e. the percentage of outgoing connections from each firm *j*.

$$(j \rightarrow S) = \frac{1}{N-1} \sum_{i \neq j} (j \rightarrow i)$$

The higher the value of the statistic, the more the company *j* is a transmitter of political risk in the network. Therefore, with this measure it is possible to identify those firms that are main transmitters of political risk to the companies in the network.

The second counting measure is calculated as the fraction of firms that Granger-cause an individual firm *j*, i.e. the percentage of incoming connections to each firm *j*.

Table 1
Descriptive statistics by sector.

Sector	Mean	Standard deviation	Min.	Max.	Nº of firms
Consumer Staples	86.26	69.76	22.01	408.27	47
Consumer Discretionary	86.32	44.74	24.09	286.25	166
Energy	100.92	41.71	26.16	242.86	57
Financials	188.90	92.34	51.18	597.34	131
Industrials	134.74	91.21	18.23	665.48	197
Real Estate	122.41	63.79	44.28	524.17	72
Materials	109.32	42.31	40.86	227.03	61
Health Care	150.17	96.33	28.18	645.08	127
Communication Services	93.37	42.36	38.61	212.29	39
Utilities	191.44	89.41	67.89	542.17	40
Information Technology	95.34	51.70	21.29	408.79	162

$$(S \rightarrow j) = \frac{1}{N-1} \sum_{i \neq j} (i \rightarrow j)$$

The higher the value of the statistic, the more the company *j* is a receiver of political risk in the network. Therefore, with this measure it is possible to identify those firms that are most vulnerable to political risk shocks from other companies in the network.

The third measure is calculated as the sum of the two previous measures and tells us which are the most (least) connected companies in the political risk network, based on the percentage of both incoming and outgoing connections.

$$(j \leftrightarrow S) = \frac{1}{2(N-1)} \sum_{i \neq j} (i \rightarrow j) + (j \rightarrow i)$$

- *Sector-conditional connections*. This statistic is similar to the ones above, but it is conditioned on the sectors to which the firms belong; thus, only connections to companies in other sectors are counted. Unlike Billio et al. (2012), we standardize by the number of companies within each sector, since this differs across sectors. Thus, the first indicator measures the fraction of outgoing connections to companies in other sectors and is defined as follows

$$\left. (j|\alpha) \rightarrow \sum_{\beta \neq \alpha} (S|\beta \right) = \frac{1}{N - l(\alpha)} \sum_{\beta \neq \alpha} \sum_{i \neq j} ((j|\alpha) \rightarrow (i|\beta))$$

where α and β are sectors and l(·) measures the number of firms within the sector. With this statistic it is possible to identify those firms that are main transmitters of political risk to companies in sectors other than the one to which the company belongs.

The second measures the fraction of incoming connections coming from other sectors and is defined as:

$$\left. \sum_{\beta \neq \alpha} (S|\beta \right) \rightarrow (j|\alpha) = \frac{1}{N - l(\alpha)} \sum_{\beta \neq \alpha} \sum_{i \neq j} ((i|\beta) \rightarrow (j|\alpha))$$

With this statistic it is possible to identify those firms that are most vulnerable to political risk shocks emanating from companies in sectors other than the one to which the company belongs.

Finally, the fraction of connections of each firm with firms in other sectors, whether incoming or outgoing, is defined as:

$$\left. (j|\alpha) \leftrightarrow \sum_{\beta \neq \alpha} (S|\beta \right) = \frac{\sum_{\beta \neq \alpha} \sum_{i \neq j} ((i|\beta) \rightarrow (j|\alpha)) + ((j|\alpha) \rightarrow (i|\beta))}{N - l(\alpha)}$$

This statistic allows us to rank the companies according to their connectivity to firms in other sectors (based on the percentage of both incoming and outgoing connections).

- *Eigenvector centrality.* This measure consists of the eigenvector of the largest eigenvalue of the adjacency matrix, scaled so that the largest value is 1 (which exists by the Perron-Frobenius theorem) because the values of the matrix are non-negative. This statistic measures a firm's importance in terms of the relevance of the firms that are connected to it (relevance measured by the number of connections a firm has to other firms).
- *Closeness centrality.* This statistic measures the average shortest path distance from a firm j to all other firms reachable from it. This measure is useful to find the best placed firms to influence the whole network more quickly. Following Billio et al. (2012) we calculate the closeness statistic as:

$$C_{jS} = \frac{\sum_{i \neq j} C_{ji}}{N-1}$$

where C_{ji} refers to the length of the shortest path distance from firm j to firm i, so the lowest the closeness measure, the closer it is to all other firms.

4. Results

The indicators of systemic risk described in section 3 above are presented here. First, we tested for Granger causality at the 5% level of statistical significance among all possible causal relationships and then we used the results of the pairwise Granger-causality tests to estimate the network of statistically significant relations among firms. We restricted our attention to those firms with few or no missing observations (as explained in Section 2).

Our large network consists of 89,109 statistically significant connections between the firms, that is, 7.4% (degree of Granger causality) of the total possible connections (1,206,702). In a first step, we explore the political risk transmission at the firm-level by means of the indicators presented above: (i) the number of connections that leave from a given company, (ii) the number of connections that enter a given company, (iii) the number of connections that pass through a given company (i.e. those that leave plus those that enter), and (iv) the eigenvector centrality indicator and the closeness centrality indicator. The former measures the importance of each company in the network by assigning relative values based on how connected each company is to the rest of the graph while the latter identifies the best placed firms to influence the whole network more quickly. We also present the results of the same indicators conditioned on the sectors to which the firms belong, so that only connections to companies in other sectors are counted. In a second step, we explore political risk transmission at the sector level by calculating the number of connections between sectors and normalizing this by using the total number of possible connections between the different sectors.

Overall, our results show that systemic political risk must be understood as a key component of systematic consumption risk in economics. Industries that are particularly sensitive to economic cycles, including Industrials, Consumer Discretionary, and Energy, play a central role in the political risk network. Therefore, it is important for firms in these sectors to diversify their political risk in order to minimize the potential negative effects of aggregate consumption risk, to which they are particularly sensitive as well. These results shed new light on the understanding of the factors driving aggregate consumption shocks in the economy, which is a fundamental element of inter temporal general equilibrium models and asset pricing studies.

4.1. Political risk transmission at the firm level

Political factors play a significant role at the firm level, there being a broad set of such factors that can affect a company's profits and sustainability, including political stability, changing policies, systems of governance, the level of bureaucracy, corruption, taxation, trade restrictions, armed conflicts, freedom of press, home market lobbying groups, among others. However, these political factors can vary in importance depending, for instance, on the sector and the goods the company produces or the services it offers. Large companies like American Express Co are always threatened by political instability. Home market lobbying practices can affect, on multiple levels, those companies in which brand reputation is crucial, such as Gap Inc., while trade union activities can be a potential political factor for companies such as Apple.

Table 2 shows the 25 companies with the largest number of outgoing connections, which are, therefore, the main transmitters of political risk in the network. The table also shows the sector in which each company operates. It is evident that Consumer Discretionary accounts for four of the six largest transmitting companies and that it is also the sector with the highest number of companies among the top 25 (a total of seven), followed by Industrials with four. Only one of the sectors is not represented among the 25 main transmitters, namely, Communication Services.

Table 3 shows the 25 companies that receive most connections from other companies, that is, those that are most susceptible to political risk shocks from other companies in the network. It is evident the sector with the largest number of companies in the top 25 is again, Consumer Discretionary, with seven companies, although in this case they do not occupy the top five positions. Here, Consumer Staples is the sector that is not represented by any firm among the 25 receiving the most political risk shocks. Note that two companies appear both among the top 25 transmitters and top 25 receivers, namely, New York Community Bancorp Inc. and American Express Co; moreover, these two companies are ranked first and third, respectively, when we sum their incoming and outgoing connections (Table 4). Both companies belong to the Financials

Table 2
Top transmitting companies.

Company name	% of connection	Nº of connections	Sector
Oxford Industries Inc.	15.03	165	Consumer Discretionary
Gap Inc.	14.57	160	Consumer Discretionary
Exelon Corp	14.48	159	Utilities
Guess? Inc.	14.39	158	Consumer Discretionary
MannKind Corp	14.39	158	Health Care
Hasbro Inc.	14.03	154	Consumer Discretionary
Hecla Mining Co	14.03	154	Materials
Stratasys Ltd	13.84	152	Information Technology
SBA Communications Corp	13.84	152	Real Estate
TrueBlue Inc.	13.48	148	Industrials
New York Community Bancorp Inc.	13.39	147	Financials
JAKKS Pacific Inc.	13.39	147	Consumer Discretionary
Align Technology Inc.	13.30	146	Health Care
RBC Bearings Inc.	13.21	145	Industrials
Brandywine Realty Trust	12.75	140	Real Estate
Washington Trust Bancorp Inc.	12.66	139	Financials
Cheesecake Factory Inc.	12.66	139	Consumer Discretionary
Dover Corp	12.57	138	Industrials
Peabody Energy Corp	12.57	138	Energy
Kimberly-Clark Corp	12.48	137	Consumer Staples
NCR Corp	12.48	137	Information Technology
Manitowoc Company Inc.	12.39	136	Industrials
MarineMax Inc.	12.30	135	Consumer Discretionary
J & J Snack Foods Corp	12.20	134	Consumer Staples
American Express Co	12.11	133	Financials

Table 3
Top most vulnerable companies.

Company name	% of connections	Nº of connections	Sector
DCP Midstream LP	17.40	191	Energy
New York Community Bancorp Inc.	17.03	187	Financials
Interpublic Group of Companies Inc.	16.39	180	Communication Services
Equity Lifestyle Properties Inc.	16.39	180	Real Estate
American Express Co	15.48	170	Financials
Universal Electronics Inc.	15.21	167	Consumer Discretionary
Abercrombie & Fitch Co	15.12	166	Consumer Discretionary
Apple Inc.	14.66	161	Information Technology
Dine Brands Global Inc.	14.57	160	Consumer Discretionary
Cedar Fair LP	14.39	158	Consumer Discretionary
Edison International	14.30	157	Utilities
Regis Corp	13.93	153	Consumer Discretionary
Federal Realty Investment Trust	13.57	149	Real Estate
Camden Property Trust	13.57	149	Real Estate
Omnicom Group Inc.	13.39	147	Communication Services
L3Harris Technologies Inc.	13.30	146	Industrials
Eagle Materials Inc.	13.30	146	Materials
M/I Homes Inc.	13.11	144	Consumer Discretionary
United Rentals Inc.	13.11	144	Industrials
Marchex Inc	13.11	144	Communication Services
Deckers Outdoor Corp	12.84	141	Consumer Discretionary
Diversified Healthcare Trust	12.66	139	Real Estate
Cigna Corp	12.57	138	Health Care
3M Co	12.57	138	Industrials
Truist Financial Corp	12.57	138	Financials

Table 4
Top most connected companies.

Company name	% of connections	Nº of connections	Sector
New York Community Bancorp Inc.	15.21	334	Financials
DCP Midstream LP	13.89	305	Energy
American Express Co	13.80	303	Financials
Equity LifeStyle Properties Inc.	13.30	292	Real Estate
Oxford Industries Inc.	13.21	290	Consumer Discretionary
MannKind Corp	13.02	286	Health Care
Interpublic Group of Companies Inc.	12.98	285	Communication Services
TrueBlue Inc.	12.75	280	Industrials
Federal Realty Investment Trust	12.39	272	Real Estate
Abercrombie & Fitch Co	12.25	269	Consumer Discretionary
Peabody Energy Corp	12.16	267	Energy
Dine Brands Global Inc.	11.98	263	Consumer Discretionary
Universal Electronics Inc.	11.93	262	Consumer Discretionary
Cedar Fair LP	11.89	261	Consumer Discretionary
Apple Inc.	11.84	260	Information Technology
Exelon Corp	11.79	259	Utilities
Marchex Inc.	11.61	255	Communication Services
Stratasys Ltd	11.43	251	Information Technology
Tractor Supply Co	11.38	250	Consumer Discretionary
Edison International	11.34	249	Utilities
Omnicom Group Inc.	11.29	248	Communication Services
Regis Corp	11.29	248	Consumer Discretionary
United Rentals Inc.	11.29	248	Industrials
Cousins Properties Inc.	11.25	247	Real Estate
Gap Inc.	11.20	246	Consumer Discretionary

sector.

Table 4 shows the 25 most connected companies in the political risk network, based on the percentage of both incoming and outgoing connections associated with each firm with respect to all possible connections. As expected from the results of the previous two indicators, the most represented sector among the top 25 is Consumer Discretionary. In contrast, Materials and Consumer Staples are underrepresented among the top 25. Note that in this case there are more instances of firms repeating from among the most vulnerable companies listed in Table 3 (16 firms coincide) than there are from among the largest transmitters of risk listed in Table 2 (9 firms coincide).

To complete the characterization of the network structure in terms of connections at the firm level we present Tables 5 and 6. Table 5 shows the top 25 companies that are the greatest transmitters to companies in sectors other than their own. As can be seen, these results are similar to those for the outgoing connections recorded in Table 2, with 23 companies coinciding on this indicator. Likewise, the sectors with the largest number of companies in the top 25 are Consumer Discretionary (with five companies), Industrials and Information Technology (with four companies each), while Communication Services are unrepresented in this table.

Table 6 lists the top 25 firms according to the number of connections that enter each company from firms in sectors other than their own, indicating which companies are most vulnerable to political risk shocks emanating from different sectors. Again, the results are similar to those that do not differentiate between sectors (see Table 3), since 23 of the companies coincide in the two tables. Likewise, the sector with most companies among the top 25 is Consumer Discretionary (with seven companies), while Consumer Staples remains without representation. Here, there are three companies that coincide with those in Table 7, i.e., leading transmitters and receivers to companies in other sectors – namely, New York Community Bancorp Inc., American Express Co and MannKind Corp, ranked first, third and fourth, respectively (see also Table 7).

Table 7 shows that when we sum incoming and outgoing connections from/to other sectors, 22 of the companies among the top 25 coincide with those in Table 4, which does not differentiate between sectors. Moreover, only nine companies coincide with those included in the outgoing connections (Table 5) and 18 with the incoming connections from other sectors (Table 6). The sector with the largest number of companies among the 25 largest according to this indicator is once again Consumer Discretionary (with seven companies) while Materials and Consumer Staples have none.

The next indicator, that of eigenvector centrality, corresponding to the eigenvector of the largest eigenvalues in the network, measures the importance of each company in the network by assigning relative values based on how connected each company is to the rest of the graph. In our estimated political risk network, the highest eigenvalue is 82.90, and its eigenvector is calculated and scaled so that the maximum value is 1 (see section 3 of the methodology). The 25 companies with the highest eigenvector values are ranked in Table 8. It is evident that all eleven sectors are represented in the table, suggesting that there is a

Table 5
Top transmitting companies to companies in other sectors.

Company name	% of connections	Nº of connections	Sector
Exelon Corp	15.01	159	Utilities
MannKind Corp	14.92	145	Health Care
Oxford Industries Inc.	14.68	137	Consumer Discretionary
RBC Bearings Inc.	14.19	128	Industrials
Gap Inc.	14.15	132	Consumer Discretionary
Hecla Mining Co	14.07	146	Materials
Guess? Inc.	14.04	131	Consumer Discretionary
SBA Communications Corp	14.02	144	Real Estate
Stratasys Ltd	13.98	131	Information Technology
TrueBlue Inc.	13.86	125	Industrials
Align Technology Inc.	13.79	134	Health Care
Hasbro Inc.	13.50	126	Consumer Discretionary
New York Community Bancorp Inc.	13.33	129	Financials
JAKKS Pacific Inc.	13.18	123	Consumer Discretionary
Brandywine Realty Trust	13.05	134	Real Estate
Dover Corp	12.97	117	Industrials
NCR Corp	12.91	121	Information Technology
Manitowoc Company Inc.	12.86	116	Industrials
Kimberly-Clark Corp	12.83	135	Consumer Staples
TESSCO Technologies Inc.	12.70	119	Information Technology
Peabody Energy Corp	12.57	131	Energy
American Express Co	12.19	118	Financials
J & J Snack Foods Corp	12.17	128	Consumer Staples
Washington Trust Bancorp Inc.	12.09	117	Financials
Universal Display Corp	12.06	113	Information Technology

Table 6
Top vulnerable companies to companies in other sectors.

Company name	% of connections	Nº of connections	Sector
DCP Midstream LP	17.47	182	Energy
New York Community Bancorp Inc.	16.94	164	Financials
Interpublic Group of Companies Inc.	16.42	174	Communication Services
Equity LifeStyle Properties Inc.	16.36	168	Real Estate
Abercrombie & Fitch Co	15.22	142	Consumer Discretionary
American Express Co	15.19	147	Financials
Universal Electronics Inc.	15.11	141	Consumer Discretionary
Edison International	14.73	156	Utilities
Dine Brands Global Inc.	14.36	134	Consumer Discretionary
Cedar Fair LP	14.04	131	Consumer Discretionary
Camden Property Trust	13.83	142	Real Estate
Eagle Materials Inc.	13.68	142	Materials
Omnicom Group Inc.	13.68	145	Communication Services
M/I Homes Inc.	13.40	125	Consumer Discretionary
Apple Inc.	13.34	125	Information Technology
United Rentals Inc.	13.30	120	Industrials
Marchex Inc.	13.30	141	Communication Services
Regis Corp	13.29	124	Consumer Discretionary
Federal Realty Investment Trust	13.15	135	Real Estate
Cigna Corp	12.96	126	Health Care
Deckers Outdoor Corp	12.75	119	Consumer Discretionary
CF Industries Holdings Inc.	12.62	131	Materials
Truist Financial Corp	12.60	122	Financials
L3Harris Technologies Inc.	12.53	113	Industrials
MannKind Corp	12.45	121	Health Care

heterogeneous spectrum in the spread of political risk across US firms. Consumer Discretionary and Industrials are the two sectors with the largest number of companies (five and four, respectively). Moreover, many firms are both central to the network and vulnerable to shocks, the case, for example, of DCP Midstream LP (Energy), Interpublic Group (Communication Services), Equity LifeStyle Properties (Real Estate), Universal Electronics and Abercrombie & Fitch Co (both Consumer Discretionary), to name the most representative examples. In contrast, the most central firms do not tend to overlap with the most frequent propagators of political risk shocks (only New York Community Bancorp Inc., American Express Co and TrueBlue Inc. are ranked high in the two categories).

Finally, the last indicator, the closeness centrality, is useful to find the best placed firms to influence the whole network more quickly. The 25 companies with the lowest closeness centrality (note that the lowest the closeness measure, the more central a firm is) are ranked in Table 9. There are few differences between companies, with 1.85 and 1.88 being the lowest and highest closeness measures, respectively. Except for Communication Services, all sectors are represented in the table, which again demonstrates the heterogeneous spectrum in the spread of political risk among US companies. The three sectors with the largest number of companies are Consumer Discretionary (5), Financials (4) and Industrials (4). Moreover, 22 firms out of 25 overlap with the top transmitters of political risk (Table 2).

Table 10 contains a summary of the indicator statistics for our sample by sector. The sectors with the lowest average number of outgoing connections are Utilities and Communication Services, while the highest average risk transmission rates are found in Industrials, Consumer Discretionary and Financials. In the case of companies most vulnerable to political risk, the sectors with the lowest average connections are Information Technology and Consumer Staples, while the sectors with the highest average number of total connections (i.e. incoming + outgoing) are Energy, Consumer Discretionary and Communication Services.

In general, sectors with firms that are most vulnerable to risk do not coincide with those that transmit most risk. Companies in Communication Services, for example, have a high mean number of incoming connections, but their mean number of outgoing connections is the second lowest of the eleven sectors. Finally, the sectors with the highest mean number of total connections are Energy and Consumer Discretionary, while those with the lowest are Utilities and Health Care.

Next, we calculate Pearson's correlation between our indicators of transmission, reception, and centrality and the average value of political risk of each company in our sample. In this way, we can establish whether our network characterization provides additional information, not provided by the original indicator of political risk. These correlations are shown in Table 11, where it can be seen that a company's average value of political risk shows almost no correlation with any of our network indicators (between −0.070 and 0.042). This result emphasizes the importance of characterizing the risk network as we have proposed in this study, since an average measure of political risk does not reflect the dynamics of risk transmission between firms. We also observe a very high correlation between the number of incoming connections to a company and its eigenvector centrality (0.946), which is not surprising since among the top 25 companies ranked according to these two

Table 7
Top connected companies to companies in other sectors.

Company name	% of connections	Nº of connections	Sector
New York Community Bancorp Inc.	15.13	293	Financials
DCP Midstream LP	13.82	288	Energy
American Express Co	13.69	265	Financials
MannKind Corp	13.68	266	Health Care
Equity LifeStyle Properties Inc.	13.15	270	Real Estate
TrueBlue Inc.	13.08	236	Industrials
Interpublic Group of Companies Inc.	12.97	275	Communication Services
Oxford Industries Inc.	12.81	239	Consumer Discretionary
Abercrombie & Fitch Co	12.43	232	Consumer Discretionary
Exelon Corp	12.18	258	Utilities
Federal Realty Investment Trust	12.17	250	Real Estate
Peabody Energy Corp	12.09	252	Energy
Universal Electronics Inc.	11.90	222	Consumer Discretionary
Cedar Fair LP	11.84	221	Consumer Discretionary
United Rentals Inc.	11.81	213	Industrials
Dine Brands Global Inc.	11.79	220	Consumer Discretionary
Tractor Supply Co	11.63	217	Consumer Discretionary
M/I Homes Inc.	11.58	216	Consumer Discretionary
Edison International	11.57	245	Utilities
Marchex Inc.	11.56	245	Communication Services
RBC Bearings Inc.	11.53	208	Industrials
Stratasys Ltd	11.42	214	Information Technology
Cigna Corp	11.37	221	Health Care
Omnicom Group Inc.	11.32	240	Communication Services
Apple Inc.	11.31	212	Information Technology

indicators there was a match in 16 cases, while there were only nine matches in the case of outgoing connections and eigenvector centrality. This result suggests that the indicator of systemic political risk is more sensitive to events of corporate vulnerability than to events of systemic impact on the market. This is natural as it is an indicator of the board of director's perception of risk and managers focus more on the risk they perceive from outside the company than on the risk the company entails for the other companies. Finally, there is a very high correlation in absolute value (−0.929) between the number of outgoing connections from a company and its closeness measure (note that the lowest the closeness measure, the closer it is to all other firms). Again, this result is not surprising since there was a match between these two indicators in 22 out of 25 cases.

Finally, we show the number of matches between the top 100 companies presenting the highest average value of political risk in the sample and the top 100 companies presenting the highest values for each of the indicators. The results are shown in Table 12 and are, in fact, similar to those obtained with the correlation analysis. Among the companies presenting the highest average political risk, very few coincide with companies presenting the highest values for the other three indicators. However, a large number of coincidences are observed between the companies most vulnerable to political risk and those with a high eigenvector centrality indicator, and the companies most transmitters and those closer to all other firms, as expected given the results in Table 11.

Table 8
Companies with highest eigenvector centrality.

Company name	Eigenvector centrality	Sector
New York Community Bancorp Inc.	1.000	Financials
Eagle Materials Inc.	0.979	Materials
DCP Midstream LP	0.977	Energy
Diversified Healthcare Trust	0.957	Real Estate
Federal Realty Investment Trust	0.952	Real Estate
Interpublic Group of Companies Inc.	0.905	Communication Services
Equity LifeStyle Properties Inc.	0.903	Real Estate
Abercrombie & Fitch Co	0.897	Consumer Discretionary
Edison International	0.894	Utilities
Universal Electronics Inc.	0.879	Consumer Discretionary
Deckers Outdoor Corp	0.865	Consumer Discretionary
Helix Energy Solutions Group Inc.	0.863	Energy
American Express Co	0.859	Financials
Truist Financial Corp	0.857	Financials
Altria Group Inc.	0.838	Consumer Staples
Danaher Corp	0.837	Health Care
CVS Health Corp	0.833	Health Care
TrueBlue Inc.	0.832	Industrials
United Rentals Inc.	0.829	Industrials
America's CAR-MART Inc.	0.826	Consumer Discretionary
3M Co	0.824	Industrials
Pitney Bowes Inc.	0.823	Industrials
Zebra Technologies Corp	0.817	Information Technology
Apple Inc.	0.810	Information Technology
Dine Brands Global Inc.	0.810	Consumer Discretionary

Table 9
Companies with lowest closeness centrality.

Company name	Closeness	Sector
Oxford Industries Inc	1.850	Consumer Discretionary
Gap Inc	1.855	Consumer Discretionary
Exelon Corp	1.857	Utilities
Guess? Inc	1.858	Consumer Discretionary
MannKind Corp	1.859	Health Care
Hecla Mining Co	1.862	Materials
Hasbro Inc	1.863	Consumer Discretionary
SBA Communications Corp	1.863	Real Estate
TrueBlue Inc	1.867	Industrials
New York Community Bancorp Inc	1.867	Financials
Stratasys Ltd	1.867	Information Technology
JAKKS Pacific Inc	1.868	Consumer Discretionary
Align Technology Inc	1.869	Health Care
RBC Bearings Inc	1.869	Industrials
Dover Corp	1.875	Industrials
Brandywine Realty Trust	1.875	Real Estate
Washington Trust Bancorp Inc	1.875	Financials
NCR Corp	1.876	Information Technology
Kimberly-Clark Corp	1.877	Consumer Staples
Cheesecake Factory Inc	1.878	Consumer Discretionary
Peabody Energy Corp	1.878	Energy
Manitowoc Company Inc	1.879	Industrials
Invesco Ltd	1.882	Financials
Calumet Specialty Products Partners LP	1.883	Energy
Hanover Insurance Group Inc	1.883	Financials

4.2. Transmission of political risk at the sector level

At the sector level, the above results are affected by the number of companies operating in each sector, since the more companies in a particular sector, the more likely that sector is to house a greater number

Table 10
Minimum, mean and maximum values of the indicators by sector.

	Out			In			Total			Eigenvector Centrality			Closeness		
Sector	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Communication Services	40	77.21	118	38	84.46	180	104	161.67	285	0.17	0.41	0.90	1.90	1.96	2.09
Consumer Discretionary	44	82.61	165	37	83.58	167	90	166.19	290	0.17	0.41	0.90	1.85	1.95	2.05
Consumer Staples	46	80.72	137	48	78.15	124	94	158.87	228	0.19	0.38	0.84	1.88	1.96	2.05
Energy	50	81.54	138	52	85.05	191	110	166.60	305	0.20	0.43	0.98	1.88	1.95	2.02
Financials	40	82.08	147	43	79.81	187	96	161.89	334	0.17	0.39	1.00	1.87	1.95	2.11
Health Care	43	78.06	158	46	79.62	138	92	157.68	286	0.19	0.38	0.84	1.86	1.96	2.09
Industrials	46	83.08	148	39	81.32	146	93	164.40	280	0.17	0.40	0.83	1.87	1.95	2.06
Information Technology	40	81.97	152	43	78.11	161	101	160.08	260	0.18	0.38	0.82	1.87	1.95	2.07
Materials	52	79.30	154	40	81.33	146	99	160.62	237	0.15	0.39	0.98	1.86	1.96	2.06
Real Estate	46	80.44	152	40	83.71	180	86	164.15	292	0.20	0.42	0.96	1.86	1.96	2.06
Utilities	44	75.08	159	53	79.78	157	116	154.85	259	0.18	0.38	0.89	1.86	1.96	2.05

Out refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

Table 11
Correlation between indicators.

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	−0.055	−0.058	−0.070	−0.066	0.042
Out	−0.055	1	0.328	0.810	0.262	−0.929
In	−0.058	0.328	1	0.820	0.946	−0.312
Total	−0.070	0.810	0.820	1	0.746	−0.756
Eigenvector Centrality	−0.066	0.262	0.946	0.746	1	−0.259
Closeness	0.042	−0.929	−0.312	−0.756	−0.259	1.000

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

Table 12
Matches among the 100 highest values of the indicators.

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	100	7	4	6	4	7
Out	7	100	17	60	16	92
In	4	17	100	56	81	13
Total	6	60	56	100	50	55
Eigenvector Centrality	4	16	81	50	100	13
Closeness	7	92	13	55	13	100

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it. In the case of Closeness, we take the 100 lowest values as the lowest the closeness measure, the closer it is to all other firms.

of companies connected to other firms in the same or in the other sectors. To prevent the results from being conditioned by the size of each sector, we calculated the number of connections between sectors and normalized this outcome by using the total number of possible connections between sectors. We then classified the results in four groups, corresponding to the quartiles of the distribution of the percentage of connections. Fig. 1 shows that the main receivers of political risk are the sectors of Energy, Consumer Staples, Real Estate, Industrials, Consumer Discretionary and Communication Services, while the main transmitters of political risk are those of Industrials, Energy and Consumer Discretionary. This indicates that some sectors act as both transmitters and receivers of political risk (i.e. Energy, Industrials and Consumer Discretionary) while others act mainly by transmitting political risk to other sectors, the case, for example, of Information Technology. Moreover, some sectors are more susceptible to receiving political risk shocks from others without apparently having much influence on these other sectors, the case, for example, of Utilities and Communication Services.

Our findings suggest that the average level of political risk does not typically align with a firm's centrality in the political risk network. This may have led previous research, including Hassan et al. (2019), to view political risk as a highly idiosyncratic phenomenon. However, our results indicate that political risk is actually related to systematic consumption shocks, with the most central actors in the political risk network belonging to industries that are particularly sensitive to economic cycles, such as Consumer Discretionary, Industrial, and Energy, with Real Estate also showing some sensitivity. This highlights the importance of considering political risk as a systemic, rather than solely individual, issue.

5. Robustness checks

Next, we explore changes in our results to the level of statistical significance of the Granger causality test (1% instead of 5%), to the choice of the number of lags in Equation (1), and to different subsamples. The results of the exercise related to the statistical significance of the Granger causality test are reported in the Appendix (Tables 1A–10A and Fig. 1A). Results show some movements of companies or sectors depending on the indicator of political risk transmission and in terms of the mean values of the indicators by sector but, in general, the results discussed above at the firm and sector level hold. Regarding the percentage of connections out of the total possible connections, as expected, it decreases from 7.4% to 2.9% when we test for Granger causality at the 1% level of statistical significance instead of 5%.

5.1. Choice of the number of lags

Next, we test the robustness of the results when the indicators are calculated using 4 lags in Equation (1). We choose $k = 4$ as the frequency

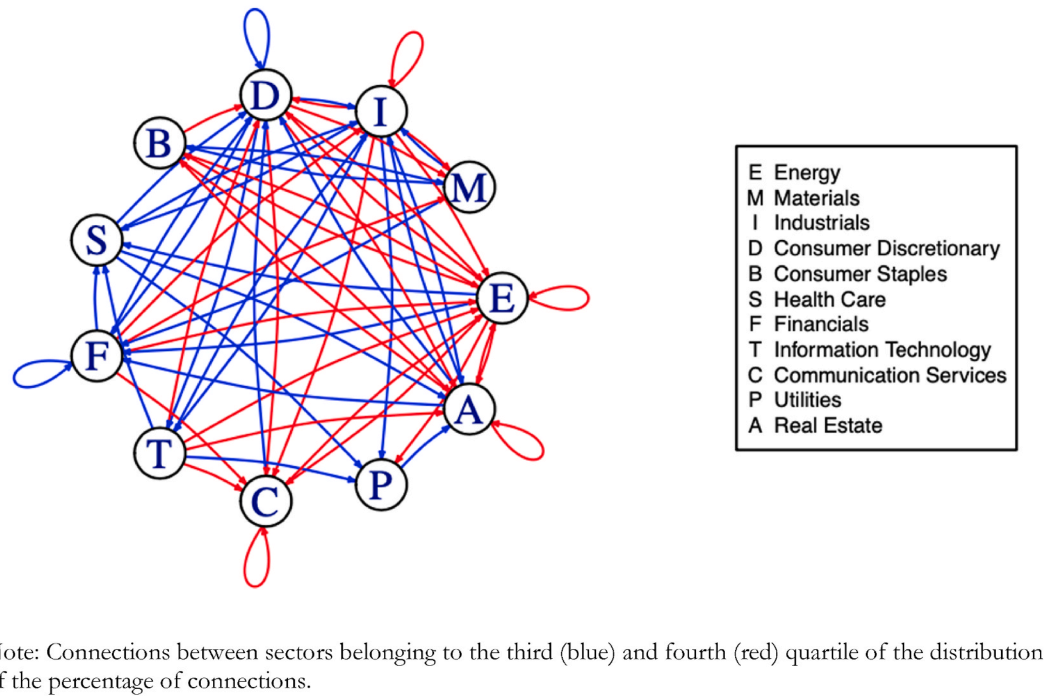


Fig. 1. Political risk transmission network between sectors
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

of the data is quarterly. Table 13 shows the correlation between our indicators of transmission, reception and centrality and the average value of political risk of each company in our sample. It is observed that the results are similar to those obtained in Table 11, where the indicators were calculated using 1 lag. Again, we observe that correlations between the average value of political risk and our network indicators are very low (between −0.058 and 0.094) indicating that an average measure of political risk does not inform on how risk is transmitted between firms. Similarly, the high correlation (in absolute value) between the number of incoming (outgoing) connections to (from) a company and its eigenvector (closeness) centrality measure holds, being 0.960 and −0.945, respectively.

At the sector level, Fig. 2 shows that the results are broadly unchanged when compared to those in Fig. 1. Real Estate, Industrials, Consumer Discretionary and Communication Services remain among the sectors most vulnerable to political risk while Industrials and Consumer Discretionary are still main transmitters. Interestingly, Health Care is the least connected sector.

5.2. Subsample analysis

Given that major crisis events happened during the sample period, such as the Global Financial Crisis and the Covid-19 pandemic, it seems natural to explore whether the main results hold over different subsample periods. We impose a minimum of 30 quarters to obtain reliable estimates of the Granger-causal relationships, so we split our sample into two sub-periods, running from Q1 2006 to Q4 2013 and from Q1 2014 to Q3 2021, respectively. Since these two subsamples include the Global Financial crisis and the Covid-19 pandemic respectively, we also analyze the period from Q1 2011 to Q3 2019, which is a tranquil period, as no major political events occurred (at least not at the scale observed in the other two periods).

The subsample analysis leads us to conclude that firms have not become highly interrelated in terms of political risk over time since the percentage of significant connections during the subsample periods remains unchanged. This percentage is 7.4 during the first subsample period, which includes the Global Financial crisis (Q1 2006 to Q4 2013), 7.8 during the second subsample period, which includes the Covid-19 pandemic (Q1 2014 to Q3 2021), and 7.4 during the tranquil period (Q1 2011 to Q3 2019). Recall that, during the total sample period, the total number of connections as a percentage of all possible connections was 7.4% so we find a similar pattern of connectedness over time, regardless of the market conditions.

Tables 14–16 show the correlation between our indicators of transmission, reception and centrality and the average value of political risk of each company during the three subsamples. In all three subsamples,

Table 13
Correlation between indicators (4 lags in the linear regressions).

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	−0.058	−0.034	−0.058	−0.046	0.094
Out	−0.058	1	0.241	0.777	0.146	−0.945
In	−0.034	0.241	1	0.798	0.960	−0.253
Total	−0.058	0.777	0.798	1	0.713	−0.751
Eigenvector Centrality	−0.046	0.146	0.960	0.713	1	−0.163
Closeness	0.094	−0.945	−0.253	−0.751	−0.163	1

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

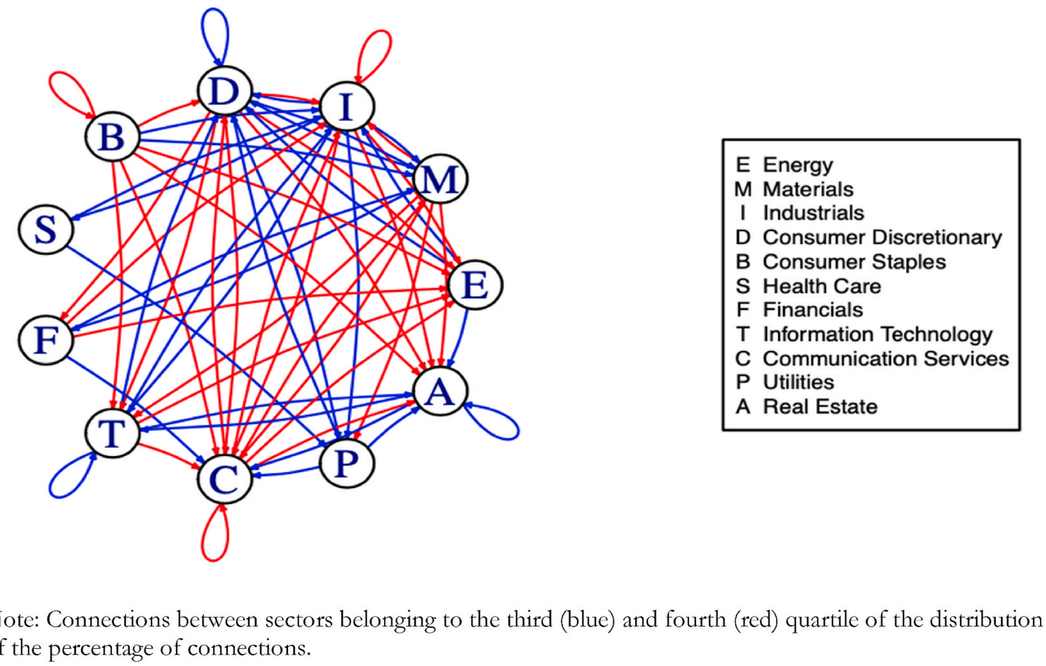


Fig. 2. Political risk transmission network between sectors (4 lags in the linear regressions)
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

correlations are low, as was already the case for the total period. Again, we conclude that an average measure of the level of political risk does not inform on how political risk is transmitted across firms. Likewise, the high correlation between some indicators mentioned above, holds.

Finally, at the sector level, the resulting network diagrams are reported in Figs. 3–5. It is evident that the networks differ slightly across periods, which is not surprising given that these are complex networks and have to be interpreted as an average of the connections during the corresponding sample period, but they are qualitatively similar to each other and to that of the total period. This result contrasts with the systemic risk networks in the financial literature, which are very dynamic, especially in times of contagion.

Consumer Discretionary and Industrials are most of the time main transmitters and receivers of political risk in the network during the three subsamples. Similarly, Communication Services is more vulnerable to political risk shocks without having much influence on the other sectors, as it was observed during the total period. Interestingly, Utilities, shown to be a sector sensitive to political risk shocks, emerges as virtually isolated in the network between Q1 2014 and Q3 2021, as is also the case with Health Care. Finally, it is observed that Energy acts as both transmitter and receiver of political risk only during the period running from Q1 2014 to Q3 2021.

6. Policy implications

Previous literature has emphasized the importance of quantifying political risk for strategic management and business continuity in the face of political uncertainty. It has also pointed to the role that firms' activities, such as political lobbying and efforts to enhance their legitimacy, can play in effectively managing political risk. In this study, we present a novel analysis of the political risk network in the US using systemic risk indicators. Our results demonstrate that political risk is not an isolated issue, but is closely connected to systematic aggregate consumption risk, which is a key concept in macroeconomics and asset pricing. We also show how political risk shocks can propagate among companies and sectors, which has important implications for managers and policymakers.

Managers seeking to minimize overall organization risk should monitor political risk since, as our results show, it could be considered as a source of systemic stress. Given that political risk is largely beyond a firm's control and cannot be easily hedged through derivatives or other financial contracts, our indicators calculated at the firm-level, provide managers with a better understanding of the exposure of the firm to political risk and allows them to identify systemically important firms that should ideally be monitored. In this sense, our indicators offer valuable information to identify both the way in which political risk might impact their own firm and the channels through it could be

Table 14
Correlation between indicators (Q1 2006 to Q4 2013).

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	0.057	0.007	0.039	0.026	−0.053
Out	0.057	1	0.346	0.822	0.318	−0.866
In	0.007	0.346	1	0.819	0.907	−0.280
Total	0.039	0.822	0.819	1	0.745	−0.699
Eigenvector Centrality	0.026	0.318	0.907	0.745	1	−0.285
Closeness	−0.053	−0.866	−0.280	−0.699	−0.285	1

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

Table 15
Correlation between indicators (Q1 2014 to Q3 2021).

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	−0.127	−0.095	−0.134	−0.092	0.112
Out	−0.127	1	0.379	0.822	0.239	−0.905
In	−0.095	0.379	1	0.838	0.889	−0.360
Total	−0.134	0.822	0.838	1	0.688	−0.755
Eigenvector Centrality	−0.092	0.239	0.889	0.688	1	−0.249
Closeness	0.112	−0.905	−0.360	−0.755	−0.249	1

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j*to all other firms reachable from it.

Table 16
Correlation between indicators (Q1 2011 to Q3 2019).

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	0.049	−0.002	0.028	0.001	−0.047
Out	0.049	1	0.415	0.842	0.427	−0.879
In	−0.002	0.415	1	0.840	0.923	−0.278
Total	0.028	0.842	0.840	1	0.801	−0.689
Eigenvector Centrality	0.001	0.427	0.923	0.801	1	−0.280
Closeness	−0.047	−0.879	−0.278	−0.689	−0.280	1

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

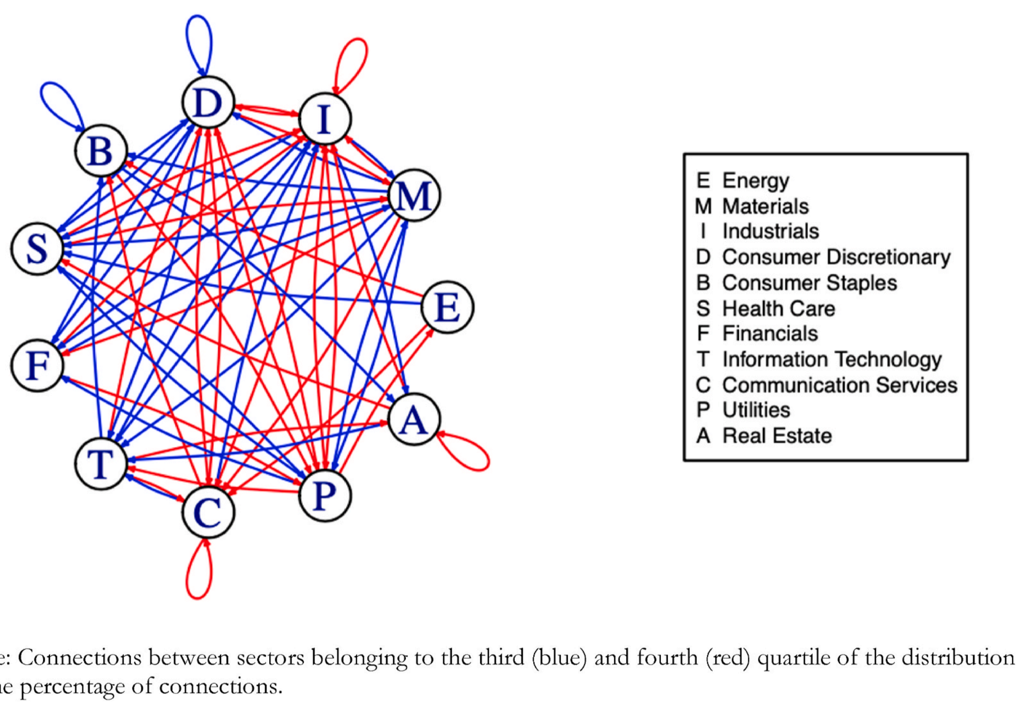
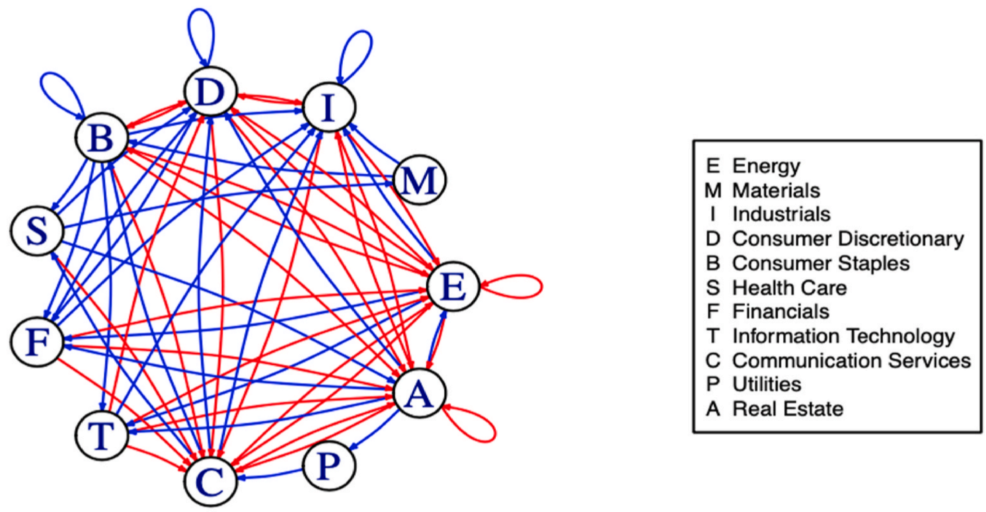


Fig. 3. Political risk transmission network between sectors (Q1 2006 to Q4 2013)
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

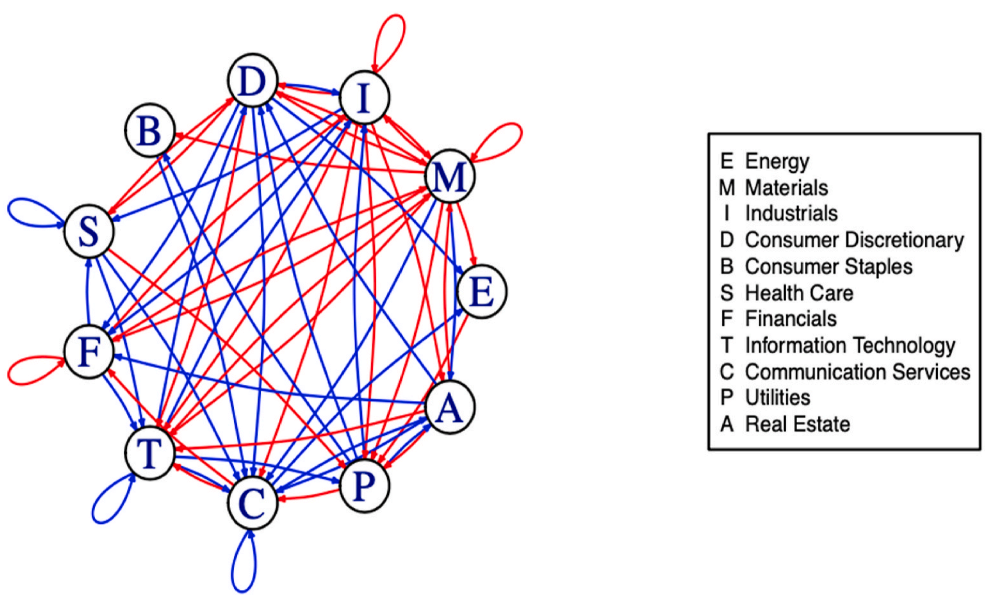
propagated (e.g. suppliers, banks, consumers. etc.). For instance, a study by the Wharton Political Risk Lab, 2021, identifies five steps for companies to manage their political risks more proactively and strategically, being the first step to identify and collect quantitative political risk indicators. Our results substantiate such claims in a quantitative manner.

Policy makers, on their side, need to understand the level of political risk and how it spreads through firms and sectors. As mentioned above, political risk can be seen as a source of systemic stress and, as such, deserves the closer examination of regulators. Regulators can monitor political risk shocks in the same way as they track the economic and solvency risks of major players in the financial sector. While such an exercise cannot be used to set, for instance, optimal capital buffers for companies in the economy, it should provide valuable information about the potential sources of future economic vulnerability for key political risk actors in the economy. It could also help political actors and governments gauge the impact of policy actions, as they should be able to warn companies particularly concerned about the consequences of such actions. Importantly, our finding that financial firms are not the



Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections.

Fig. 4. Political risk transmission network between sectors (Q1 2014 to Q3 2021)
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections.

Fig. 5. Political risk transmission network between sectors (Q1 2011 to Q3 2019)
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

only (or even the most prominent) source of systemic political risk, as tends to be the case in the systemic risk literature in the field of finance, should warn regulators as they normally focus on monitoring exclusively the risk of such companies.

7. Conclusions

In this paper, we investigate political risk from a systemic perspective. Specifically, we analyze political risk propagation across US firms and sectors and characterize the political risk network by means of systemic risk indicators. These systemic risk indicators calculated for each individual firm allow us to identify which actors are the most systemically important (vulnerable) in the US political risk network and detect patterns of risk propagating both within and between economic sectors. Our results provide clear evidence of the transmission of political risk between US companies. Of the total possible connections between the 1099 firms in our sample, 89,109 significant connections, that is, 7.4%, were documented using bivariate Granger causality tests at the 5% level of statistical significance.

At the firm level, we show that the Consumer Discretionary sector houses the largest number of companies among the top 25 for each systemic risk indicator, measuring incoming, outgoing and total connections as well as centrality. This result holds when we only consider connections to/from companies in other sectors. Two firms in the Financials sector, New York Community Bancorp Inc. and American Express Co, stand out among the top 25 companies on each of the systemic indicators and the indicator of eigenvector centrality. Interestingly, all sectors are represented among the top 25 firms presenting highest eigenvector centrality in our network; yet, eigenvector centrality is more closely related to the indicator of incoming connections than it is with that of outgoing connections. Contrary to the systemic financial risk literature, in our estimations financial services are neither the only nor the most relevant source of systemic political risk.

We also show that our network characterization provides additional information, insights not provided by the raw indicator of political risk used by Hassan et al. (2019) that serves as a time-average value of the political risk of each firm. Indeed, this mean value shows almost no correlation with any of our three indicators. This particular outcome highlights, therefore, the importance of characterizing the risk network, since a mean measure of political risk does not reflect the dynamics of risk transmission between companies, nor does it allow us to consider political risk as systemic in nature.

Our analysis of political risk transmission at the sector level (controlling for the size of each sector) reveals Consumer Discretionary and Industrials sectors as being the main transmitters and receivers of political risk during the whole period. The Energy sector joined them during the period from Q1 2014 to Q3 2021. Communication Services is more sensitive to receiving political risk spillovers from other sectors but without affecting the other sectors to any great extent. Finally, Utilities and Health Care are practically isolated from the other sectors between Q1 2014 to Q3 2021.

Our results are critical for managers and policy makers alike. The former are able to identify whether the sector in which they operate is a leading player in the political risk network and they can even identify specific companies that should ideally be monitored so as to anticipate the emergence of political risk concerns.[2] Meanwhile, regulators can use the information provided by our analysis on how political risk spreads across firms and sectors for monitoring purposes and to assess the impact of policy interventions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

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Appendix

Table 1A
Top transmitting companies (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
Gap Inc	9.11%	100	Consumer Discretionary
Exelon Corp	8.47%	93	Utilities
MannKind Corp	7.83%	86	Health Care
Hasbro Inc	7.65%	84	Consumer Discretionary
JAKKS Pacific Inc	7.19%	79	Consumer Discretionary
Washington Trust Bancorp Inc	7.01%	77	Financials
TrueBlue Inc	6.92%	76	Industrials
Guess? Inc	6.92%	76	Consumer Discretionary
Manitowoc Company Inc	6.83%	75	Industrials
Cheesecake Factory Inc	6.83%	75	Consumer Discretionary
Stratasys Ltd	6.83%	75	Information Technology
Hecla Mining Co	6.65%	73	Materials
New York Community Bancorp Inc	6.65%	73	Financials
SBA Communications Corp	6.65%	73	Real Estate
Oxford Industries Inc	6.56%	72	Consumer Discretionary
RBC Bearings Inc	6.56%	72	Industrials
Dover Corp	6.47%	71	Industrials
Brandywine Realty Trust	6.47%	71	Real Estate
Markel Corp	6.38%	70	Financials
Jack Henry & Associates Inc	6.19%	68	Information Technology
USANA Health Sciences Inc	6.19%	68	Consumer Staples
American Express Co	6.10%	67	Financials
Hanover Insurance Group Inc	6.01%	66	Financials
Peabody Energy Corp	6.01%	66	Energy
PROG Holdings Inc	5.92%	65	Financials

[2] Indicators for the 1099 firms in the sample are available upon request.

Table 2A
Top most vulnerable companies (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
DCP Midstream LP	11.02%	121	Energy
Equity LifeStyle Properties Inc	10.02%	110	Real Estate
New York Community Bancorp Inc	10.02%	110	Financials
Apple Inc	9.74%	107	Information Technology
American Express Co	9.29%	102	Financials
Dine Brands Global Inc	9.29%	102	Consumer Discretionary
Interpublic Group of Companies Inc	8.65%	95	Communication Services
Eagle Materials Inc	8.38%	92	Materials
Edison International	8.29%	91	Utilities
Omnicom Group Inc	8.20%	90	Communication Services
Cedar Fair LP	8.11%	89	Consumer Discretionary
Universal Electronics Inc	7.92%	87	Consumer Discretionary
Abercrombie & Fitch Co	7.83%	86	Consumer Discretionary
Diversified Healthcare Trust	7.65%	84	Real Estate
M/I Homes Inc	7.56%	83	Consumer Discretionary
Federal Realty Investment Trust	7.29%	80	Real Estate
Helix Energy Solutions Group Inc	7.01%	77	Energy
Harsco Corp	6.65%	73	Industrials
L3Harris Technologies Inc	6.47%	71	Industrials
Camden Property Trust	6.47%	71	Real Estate
CVS Health Corp	6.38%	70	Health Care
Peabody Energy Corp	6.38%	70	Energy
Danaher Corp	6.19%	68	Health Care
Regis Corp	6.19%	68	Consumer Discretionary
UDR Inc	6.19%	68	Real Estate

Table 3A
Top most connected companies (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
DCP Midstream LP	8.42%	185	Energy
New York Community Bancorp Inc	8.33%	183	Financials
Equity LifeStyle Properties Inc	7.74%	170	Real Estate
American Express Co	7.70%	169	Financials
Apple Inc	7.47%	164	Information Technology
Dine Brands Global Inc	7.24%	159	Consumer Discretionary
Interpublic Group of Companies Inc	6.65%	146	Communication Services
Omnicom Group Inc	6.60%	145	Communication Services
Edison International	6.51%	143	Utilities
Gap Inc	6.38%	140	Consumer Discretionary
Exelon Corp	6.38%	140	Utilities
TrueBlue Inc	6.33%	139	Industrials
Federal Realty Investment Trust	6.24%	137	Real Estate
Abercrombie & Fitch Co	6.24%	137	Consumer Discretionary
Peabody Energy Corp	6.19%	136	Energy
Universal Electronics Inc	6.15%	135	Consumer Discretionary
Cedar Fair LP	6.10%	134	Consumer Discretionary
MannKind Corp	5.97%	131	Health Care
Cheesecake Factory Inc	5.92%	130	Consumer Discretionary
M/I Homes Inc	5.78%	127	Consumer Discretionary
Eagle Materials Inc	5.69%	125	Materials
Stratasys Ltd	5.60%	123	Information Technology
Diversified Healthcare Trust	5.60%	123	Real Estate
NCR Corp	5.51%	121	Information Technology
UDR Inc	5.51%	121	Real Estate

Table 4A
Top transmitting companies to companies in other sectors (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
Gap Inc	9.32%	87	Consumer Discretionary
Exelon Corp	8.78%	93	Utilities
MannKind Corp	8.23%	80	Health Care
Hasbro Inc	7.40%	69	Consumer Discretionary
Stratasys Ltd	7.36%	69	Information Technology
TrueBlue Inc	7.21%	65	Industrials
JAKKS Pacific Inc	7.07%	66	Consumer Discretionary

(*continued on next page*)

Table 4A (*continued*)

Company name	Percentage of connections	Number of connections	Sector
Manitowoc Company Inc	6.98%	63	Industrials
RBC Bearings Inc	6.98%	63	Industrials
Guess? Inc	6.97%	65	Consumer Discretionary
Hecla Mining Co	6.84%	71	Materials
Washington Trust Bancorp Inc	6.71%	65	Financials
Dover Corp	6.65%	60	Industrials
SBA Communications Corp	6.62%	68	Real Estate
New York Community Bancorp Inc	6.61%	64	Financials
Brandywine Realty Trust	6.52%	67	Real Estate
Oxford Industries Inc	6.43%	60	Consumer Discretionary
Cheesecake Factory Inc	6.32%	59	Consumer Discretionary
Lincoln Educational Services Corp	6.32%	59	Consumer Discretionary
Hanover Insurance Group Inc	6.20%	60	Financials
Jack Henry & Associates Inc	6.19%	58	Information Technology
Kimberly-Clark Corp	6.18%	65	Consumer Staples
Peabody Energy Corp	6.14%	64	Energy
PROG Holdings Inc	6.10%	59	Financials
Markel Corp	6.10%	59	Financials

Table 5A
Top vulnerable companies to companies in other sectors (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
DCP Midstream LP	10.94%	114	Energy
Equity LifeStyle Properties Inc	10.22%	105	Real Estate
New York Community Bancorp Inc	9.71%	94	Financials
Dine Brands Global Inc	9.43%	88	Consumer Discretionary
American Express Co	9.40%	91	Financials
Interpublic Group of Companies Inc	8.77%	93	Communication Services
Edison International	8.59%	91	Utilities
Eagle Materials Inc	8.57%	89	Materials
Universal Electronics Inc	8.47%	79	Consumer Discretionary
Apple Inc	8.32%	78	Information Technology
Omnicom Group Inc	8.30%	88	Communication Services
Abercrombie & Fitch Co	8.15%	76	Consumer Discretionary
M/I Homes Inc	7.93%	74	Consumer Discretionary
Cedar Fair LP	7.93%	74	Consumer Discretionary
Diversified Healthcare Trust	7.40%	76	Real Estate
Federal Realty Investment Trust	7.21%	74	Real Estate
Helix Energy Solutions Group Inc	6.81%	71	Energy
CVS Health Corp	6.79%	66	Health Care
Harsco Corp	6.76%	61	Industrials
Camden Property Trust	6.62%	68	Real Estate
Regal Rexnord Corp	6.54%	59	Industrials
UDR Inc	6.52%	67	Real Estate
Danaher Corp	6.38%	62	Health Care
Cigna Corp	6.28%	61	Health Care
International Paper Co	6.26%	65	Materials

Table 6A
Top connected companies to companies in other sectors (at the 99% confidence interval)

Company name	Percentage of connections	Number of connections	Sector
DCP Midstream LP	8.25%	172	Energy
New York Community Bancorp Inc	8.16%	158	Financials
Equity LifeStyle Properties Inc	7.74%	159	Real Estate
American Express Co	7.70%	149	Financials
Dine Brands Global Inc	7.29%	136	Consumer Discretionary
Apple Inc	6.78%	127	Information Technology
TrueBlue Inc	6.65%	120	Industrials
Edison International	6.61%	140	Utilities
Omnicom Group Inc	6.60%	140	Communication Services
Interpublic Group of Companies Inc	6.60%	140	Communication Services
Exelon Corp	6.56%	139	Utilities
Gap Inc	6.54%	122	Consumer Discretionary
Universal Electronics Inc	6.43%	120	Consumer Discretionary
Abercrombie & Fitch Co	6.38%	119	Consumer Discretionary
MannKind Corp	6.33%	123	Health Care
Peabody Energy Corp	6.19%	129	Energy

(*continued on next page*)

Table 6A (*continued*)

Company name	Percentage of connections	Number of connections	Sector
Cedar Fair LP	6.16%	115	Consumer Discretionary
M/I Homes Inc	6.06%	113	Consumer Discretionary
Federal Realty Investment Trust	6.04%	124	Real Estate
Eagle Materials Inc	5.88%	122	Materials
RBC Bearings Inc	5.88%	106	Industrials
Stratasys Ltd	5.87%	110	Information Technology
BlueLinx Holdings Inc	5.76%	104	Industrials
NCR Corp	5.76%	108	Information Technology
Manitowoc Company Inc	5.60%	101	Industrials

Table 7A
Companies with highest eigenvector centrality (at the 99% confidence interval)

Company name	Eigenvector centrality	Sector
Diversified Healthcare Trust	1.000	Real Estate
Eagle Materials Inc	0.999	Materials
Helix Energy Solutions Group Inc	0.888	Energy
Federal Realty Investment Trust	0.855	Real Estate
Pool Corp	0.781	Consumer Discretionary
Altria Group Inc	0.760	Consumer Staples
CVS Health Corp	0.739	Health Care
New York Community Bancorp Inc	0.727	Financials
Omega Healthcare Investors Inc	0.724	Real Estate
Edison International	0.713	Utilities
Autodesk Inc	0.711	Information Technology
DCP Midstream LP	0.710	Energy
Danaher Corp	0.702	Health Care
Deckers Outdoor Corp	0.699	Consumer Discretionary
America's CAR-MART Inc	0.662	Consumer Discretionary
Equity LifeStyle Properties Inc	0.639	Real Estate
Regal Rexnord Corp	0.636	Industrials
Truist Financial Corp	0.633	Financials
Pitney Bowes Inc	0.632	Industrials
Abercrombie & Fitch Co	0.624	Consumer Discretionary
Greenbrier Companies Inc	0.613	Industrials
Whiting Petroleum Corp	0.610	Energy
American Express Co	0.609	Financials
Zions Bancorporation NA	0.609	Financials
Masco Corp	0.605	Industrials

Table 8A
Companies with lowest closeness centrality (at the 99% confidence interval)

Company name	Closeness	Sector
Gap Inc	2.148	Consumer Discretionary
Exelon Corp	2.155	Utilities
Hasbro Inc	2.183	Consumer Discretionary
MannKind Corp	2.213	Health Care
Manitowoc Company Inc	2.219	Industrials
Hecla Mining Co	2.242	Materials
Brandywine Realty Trust	2.245	Real Estate
E. W. Scripps Co	2.248	Communication Services
Cheesecake Factory Inc	2.249	Consumer Discretionary
RBC Bearings Inc	2.249	Industrials
Washington Trust Bancorp Inc	2.250	Financials
JAKKS Pacific Inc	2.250	Consumer Discretionary
Kimberly-Clark Corp	2.254	Consumer Staples
Coherent Inc	2.262	Information Technology
Stratasys Ltd	2.265	Information Technology
TrueBlue Inc	2.267	Industrials
SBA Communications Corp	2.267	Real Estate
Oxford Industries Inc	2.268	Consumer Discretionary
JPMorgan Chase & Co	2.274	Financials
Guess? Inc	2.274	Consumer Discretionary
Dover Corp	2.280	Industrials
Markel Corp	2.281	Financials
NETGEAR Inc	2.282	Information Technology
Lincoln Educational Services Corp	2.286	Consumer Discretionary
PROG Holdings Inc	2.287	Financials

Table 9A
Minimum, mean and maximum values of the indicators by sector (at the 99% confidence interval)

	Out			In			Total			Eigenvector Centrality			Closeness		
Sector	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Communication Services	13	30.41	64	13	36.03	95	32	66.44	146	0.06	0.21	0.54	2.25	2.56	2.73
Consumer Discretionary	8	33.13	100	10	33.93	102	18	67.07	159	0.06	0.20	0.78	2.15	2.54	2.89
Consumer Staples	10	30.89	68	10	30.15	63	24	61.04	112	0.05	0.17	0.76	2.25	2.56	2.87
Energy	10	30.65	66	14	32.74	121	28	63.39	185	0.05	0.21	0.89	2.32	2.56	2.82
Financials	8	31.29	77	11	30.39	110	19	61.68	183	0.04	0.17	0.73	2.25	2.56	2.88
Health Care	11	30.17	86	6	30.30	70	21	60.46	131	0.04	0.18	0.74	2.21	2.56	2.78
Industrials	7	34.01	76	9	33.01	73	23	67.02	139	0.04	0.19	0.64	2.22	2.53	2.92
Information Technology	9	32.25	75	8	29.96	107	18	62.21	164	0.04	0.17	0.71	2.26	2.54	2.92
Materials	10	31.85	73	7	32.54	92	17	64.39	125	0.04	0.19	1.00	2.24	2.55	2.78
Real Estate	10	31.86	73	11	33.94	110	21	65.81	170	0.07	0.21	1.00	2.24	2.56	2.80
Utilities	13	31.40	93	16	32.45	91	29	63.85	143	0.07	0.18	0.71	2.15	2.56	2.74

Out refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

Table 10A
Correlation between indicators

	Average risk	Out	In	Total	Eigenvector Centrality	Closeness
Average risk	1	−0.040	−0.034	−0.043	−0.052	0.046
Out	−0.040	1	0.453	0.839	0.263	−0.918
In	−0.034	0.453	1	0.865	0.839	−0.381
Total	−0.043	0.839	0.865	1	0.660	−0.749
Eigenvector Centrality	−0.052	0.263	0.839	0.660	1	−0.232
Closeness	0.046	−0.918	−0.381	−0.749	−0.232	1

Average risk refers to the average value of political risk, *Out* refers to connections that leave from a given company, *In* refers to connections that enter a given company, *Total* refers to connections that pass through a given company (incoming and outgoing). *Eigenvector Centrality* refers to the eigenvector centrality indicator. *Closeness* refers to the average shortest path distance from a firm *j* to all other firms reachable from it.

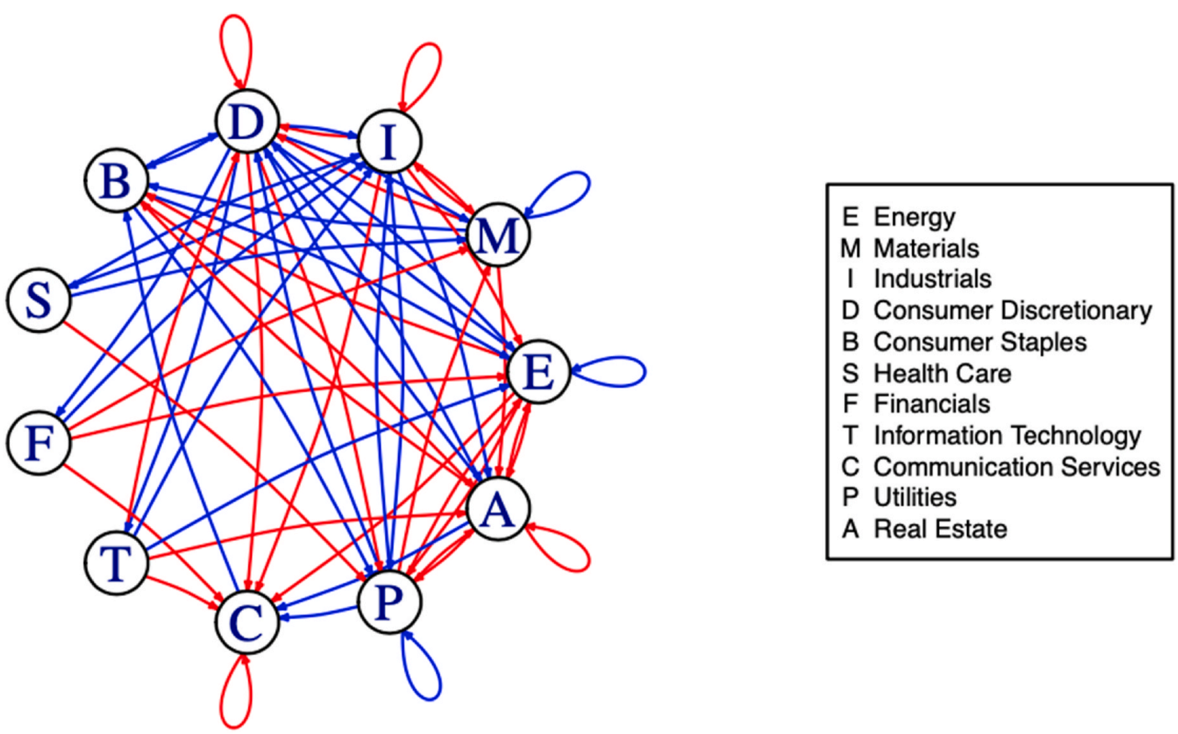

Fig. 1A. Political risk transmission network between sectors
Note: Connections between sectors belonging to the third (blue) and fourth (red) quartile of the distribution of the percentage of connections.

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