Firm-level Political Risk and Systemic Risk: The Role of Board Interlocks and Corporate Political Activity

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Abstract

We investigate the effect of firm-level political risk on systemic risk contribution. Using a 20-year firm-quarter panel of 5445 US listed firms, we document a significantly positive association between firm-level political risk and systemic risk. The results remain consistent against a battery of robustness tests, as well as a propensity score matching and instrumental variable analysis for mitigating endogeneity concerns. We identify two potential non-business channels which may exacerbate this association. First, consistent with the literature on board interlocks which evidence information transmission and diffusion of corporate practices across firms, we find the positive association between political risk and systemic risk to be amplified in the presence of strong board connections. Next, we examine the role of corporate political activity, specifically, lobbying and political campaign contributions. We find some evidence that corporate political activity magnifies the association between political risk and systemic risk. Firms occupying influential positions within the lobbying and campaign contribution network exhibit a pronounced effect of political risk on systemic risk. Overall, our study provides novel insights into the systemic importance of firm-level political risk.

Keywords: Firm-level Political Risk, Systemic Risk, Corporate Political Activity, Board Interlock Networks

JEL Classification Codes: G1, G2, G3, P16

1.Introduction

Traditional theories of corporate finance are centred around the firm as being simply a 'nexus of contracts' (Jensen & Meckling, 1976). Theories seeking to explain corporate firm behaviour have, however, ignored the political forces surrounding and possibly shaping corporate outcomes (Zingales, 2017). Governments, both national and transnational, wield the power to shape corporate law and business policies, thus effectively setting up the playground as well as the 'rules of the game' for firms (Pástor & Veronesi, 2012). Ergo, corporate behaviour and outcomes are vulnerable to shifts in the political climate, which may be triggered by changes in government (elections, for instance), possibility of and shifts in policy, and geopolitical tensions, to name a few. Indeed, political risk ranks high in the hierarchy of risks perceived by top management across firms globally, even more so since the global financial crisis (Giambona et al., 2017). Extant literature finds that political uncertainty affects asset prices (Pástor & Veronesi, 2012), as well as corporate behaviour (Bonaime et al., 2018; Gulen & Ion, 2016; Jens, 2017; Julio & Yook, 2012). However, the above strand of literature focuses on macro-level, as opposed to firm-specific or idiosyncratic political risk. Although political risk may originate from macro sources, such as elections or political crises, firms may differ in their exposure to such risk. Certain industries, such as pharmaceuticals, may have higher political risk because of their sensitivity to regulation. Firms reliant on government contracts, too, suffer from greater exposure to government policy. The idea that firms may differ in their exposure to political risk was first discussed at length by Hassan et al. (2019). Their study developed measures of firm-level political risk by quantifying the proportion of discussion during earnings conference calls which were on topics of political nature. Hassan et al. (2019) find that 91.69% of variation in political risk cannot be explained away by sector or time-level dimensions, and is in fact idiosyncratic to the firm. A wealth of literature has since documented the effects that firm-level political risk has on corporate behaviour, including capital investment (Hassan et al., 2019), operating investment (Banerjee & Dutta, 2022), choice of debt instruments (Huang et al., 2023a), and dividend decisions (Ahmad et al., 2023). Gorbatikov et al. (2019) , further, finds that firm-level political risk is priced into firm stock returns. Relatively little, however, is known about whether firm-specific political risk can result in propagation, or spillovers, of risk across firm boundaries. This forms the subject of our present study.

Over the last decade, firms have increasingly become exposed to the political system. Perception of political risk by firm management has increased (Giambona et al., 2017), and so has corporate political activity. As Hassan et al. (2019) document, firms facing higher political risk also engage in active lobbying, and donate to political campaigns as a way to manage their exposure. Indeed, both the share of firms engaging in, as well as the expenditure towards lobbying has increased over the past decade (Cao et al., 2018; Kong et al., 2017). Data sourced from the Center for Responsive Politics (CRP, hereafter) reveal that business interests have spent a record USD 3.5 billion towards federal political contributions during the 2022 election cycle alone, which far outweighs contributions from labour and other sources[3]. As demonstrated by Chuliá et al. (2023), firms have become increasingly intertwined with each other within the political network, which raises the possibility of propagation of political risk from influential firms to others connected to them. Even within a weak political network, firms are connected through business relationships, such as lenders with borrowers, and suppliers with customers. Firms may also be connected through common board members, all of which may exacerbate the risk propagation through the political network. Two recent studies have examined propagation of firm-level political risk. The first is Chulia et al. (2023), who employ tools of network analysis to demonstrate causal propagation (in the Granger sense) of firm-level political risk. Their work also identifies firms occupying influential as well as vulnerable positions within the political risk network. The second work we refer to is Gad et al. (2023). Their study on private credit markets depicts the transmission of firm-level political risk through lending relationships. Given the inevitable rise of the political network, it becomes imperative to study whether firm financial risk may propagate throughout the political network. In other words, we ask the question: does firm-specific political risk have any association with systemic risk contribution by a firm?

Extant literature on systemic risk has been almost exclusively focused on risk propagation in the banking and financial sector (Adrian & Brunnermeier, 2016; Anginer et al., 2014; Bostandzic & Weiß, 2018; Cai et al., 2018; Varotto & Zhao, 2018a). The focus on systemic risk among firms in the financial sector is understandable, considering their economic significance, interconnectedness through interbank and lender-borrower relationships, and the market-wide ramifications of a systemic event. Such ramifications, however, extend to non-financial firms (NFCs, hereafter) as well. NFCs have complicated linkages to financial firms through lending relationships, as well as to other NFCs through trade credit and supply chain associations. As such, NFCs may occupy influential positions within the economic network, thus opening up

[3] For the original article and a definition of 'business interests', the reader is referred to the CRP website: https://www.opensecrets.org/news/2023/01/business-interests-spent-3-5-billion-on-federal-political-contributions-during-the-2022-cycle/

the very real possibility of propagation of shocks throughout the network. For instance, a shock originating at a debt-ridden non-financial firm may result in an increase in financial risk of its lenders, creditors, and debtors. Conversely, a firm that is otherwise in good financial health may witness a spike in financial risk because it is connected to, and heavily reliant, on trade credit from a failing firm. The possibility that non-financial firms, too, may contribute to a systemic event, has been the focus of a relatively recent strand of literature. In a theoretical work, Acemoglu et al. (2015) demonstrate how the magnitude of shocks affecting NFCs affect financial system stability. Jacobson & von Schedvin (2015) provide evidence of bankruptcy risk contagion across trade credit networks. As such, interfirm trade linkages are an important channel for default risk propagation, as further evidenced by Hazama & Uesugi (2017). Finally, the systemic risk connection of NFCs with the financial sector has been portrayed in Dungey et al. (2018), and Dungey et al. (2020). Given the systemic importance of NFCs, an examination of the drivers of systemic risk becomes crucial, both for firm management to assess their risk exposure, and, more importantly, for policymakers, to identify and monitor systemically important firms within the network. To the best of our knowledge, the first study undertaken to this effect is Dungey et al. (2022). In their analysis of S&P 1500 firms, they identify firm characteristics which are associated with systemic risk contribution. Larger firms, and firms with greater trade credit linkages are found to be of greater systemic importance. Their results are consistent with the "too-big-to-fail" hypothesis, which stresses that large firms are systemically riskier as they benefit from the possibility of a bailout in case of distress. The study also differentiates between factors which amplify systemic importance of a firm, from those which exacerbate vulnerability to market-wide shocks. In the energy sector, Caporin et al. (2023) probe the evolution of systemic risk drivers for US oil and gas firms, over various periods of tension in energy markets. Our study introduces political risk as an additional factor influencing systemic risk of a firm. Drawing from the literature on political risk, corporate political activity, and political risk transmission (Chulia et al. 2023; Gad et al. 2023), we empirically investigate whether firm-level political risk affects firm systemic risk.

Ex-ante, the association between political risk and systemic risk is unclear. On one hand, one may argue for the "too-big-to-fail" and the "too-interconnected-to-fail" hypotheses: firms which are larger and more profitable may also have greater political risk, both because they are more connected within the network and thus, more exposed to the political system, and because they have the need for and the means to engage in political activities such as lobbying and campaign donations. Firms which are politically connected or those which engage in corporate political activities enjoy preferential access to bank finance (Claessens et al., 2008) and suffer from potential moral hazard problems (Kostovetsky, 2015), which may result in such firms being heavily debt-ridden. This may aggravate risk contagion, should the firm fall into distress. Moreover, politically connected firms benefit from lower scrutiny from regulators (Lamberta, 2019; Wu et al., 2016; Yu & Yu, 2011), and possess higher risk-taking (Boubakri et al., 2013). If such firms occupy central positions within the risk network, risk contagion may be amplified, which indicates a positive political-systemic risk association. On the other hand, political connections also relate to high survival rates for connected firms (Akcigit et al., 2023), as such firms may be preferentially bailed out to avoid a systemic event (Blau et al., 2013). Taking this into consideration, and to the extent that corporate political activity relates with political risk, one may argue for a negative association between political risk and systemic risk. We probe this empirical question by analysing a quarterly sample of 5,445 unique US listed firms over a twenty-year period spanning 2002-2021. We employ firm-level political risk as developed by Hassan et al. (2019) as the measure of political risk. To quantify systemic risk contribution by each firm, we employ ΔCoVaR, proposed by Adrian & Brunnermeier (2016). ΔCoVaR captures the vulnerability of the financial system (market) to a firm-level shock. We find that firm-level political risk has a strong positive association with systemic risk, after controlling for conventional risk factors. The findings are robust to multiple measures of systemic risk (described in detail in forthcoming sections), regression specifications, and additional controls for market-wide policy uncertainty. We attempt to manage endogeneity concerns by employing multiple fixed effects specifications, and instrumental variable analysis to further establish causality. Our results continue to hold up in a propensity score matched sample, alleviating concerns of functional form misspecification.

Having established a positive association, we next delve deeper to identify potential channels which amplify risk propagation. Traditional firm network channels studied in the literature include those arising due to the natural course of business – bank and trade credit. We study another mechanism of firm network connection, namely, board interlocks. Unlike credit-based networks, which arise due to business and lending relationships, board interlocks are present even between firms operating in unrelated lines of business. Interlocked boards arise primarily when a director or a top executive sits on the boards of multiple firms. This constitutes an employment connection between these firms as the director is 'shared'. Existing literature on board interlocks offer two perspectives. First, the presence of common directors opens up opportunities for information leakage through the firm network. Cheng et al. (2019) term this the "network view". Information spillages through director networks have been well documented in the literature (Akbas et al., 2016; Cheng et al., 2019; Haunschild & Beckman, 1998; Larcker et al., 2013). While transmission of information through the director network may benefit the firm by reducing information frictions and providing access to specialized knowledge (Amin et al., 2020; Chang & Wu, 2021; Dass et al., 2014), directors could potentially transmit non-public information through their private networks (Akbas et al., 2016; Cheng et al., 2019; Cohen et al., 2008). Consistent with this argument, recent literature finds that systemic risk is higher for firms with well-connected boards (Adasi Manu & Qi, 2023; Guo et al., 2024). To the extent that information shared among directors relate with firm characteristics and risk factors, the political risk-systemic risk association may be amplified in the presence of a well-connected board. Second, shared directors may also lead to diffusion of accounting practices and corporate policies across connected firms (Adasi Manu & Qi, 2023; Chiu et al., 2013; Fracassia, 2017). Connected firms may, thus, be similar in terms of corporate practices, and consequently, in performance outcomes. The incidence of financial weakness at a firm which occupies a central position within the board interlocking network may induce perception of similar weakness at connected firms, resulting in a systemic event. Using director employment data from BoardEx, we find that the positive association between firm-level political risk and systemic risk is amplified for firms with well-connected boards, which highlights the importance of board networks in aggravating systemic risk transmission through political risk networks.

In their seminal paper on measurement of firm level political risk, Hassan et al. (2019) study the relationship between political risk and corporate political activity (CPA, hereafter). They find that firms with high political risk also increase lobbying activity, and donate more to political campaigns, in an attempt to manage their political exposure. This could have two implications for systemic risk. On one hand, in the event that increased CPA does help manage firms' political exposure, one may expect systemic risk contribution to be lower for firms actively engaged in lobbying and/or political campaign contributions. Indeed, as documented by Gorbatikov et al. (2019), campaign contributions help mitigate the negative impact of firm level political risk for abnormal stock price returns, essentially alleviating vulnerability of such firms to political shocks. On the other hand, however, CPA may potentially strengthen the political network further by bridging connections between firms that are otherwise unrelated, but who lobby towards the same cause or donate to the same politician. Data on lobbying expenditures and issues reported by the Center for Responsive Politics (CRP) reveal that firms lobby towards a broad range of bills and issues, including topics which fall outside their direct line of business[4]. As an illustration, lobbying data for American Airlines Group show that, in 2020, the group actively lobbied for issues related to aviation, trade, taxes, and transportation. But they also did so for issues of retirement, homeland security, and finance. Firms which lobby more, both in terms of expenditure and the number of issues lobbied, occupy influential positions within the lobbying network. Consequently, a shock idiosyncratic to such a firm may aggravate risk contagion through their connections. Firms may also be "systemic as a herd" (Adrian & Brunnermeier, 2016) on account of a common shock arising from certain lobbying issues. A similar outcome is possible for corporate political contributions to federal candidates. Firms, even from unrelated industries, are inextricably linked because of contributions made by their political action committees (PACs) to common federal candidates. To this end, we first empirically examine whether corporate lobbying activity affects the association between firm level political risk and systemic risk. Using data on quarterly lobbying expenditures from CRP, we find that systemic risk for politically risky firms is heightened in the presence of lobbying. We further employ network tools on firm-level lobbying issues data to identify firms which occupy central positions within the lobbying issues network. Similar to results for lobbying expenditures, we find that the association between firm level political risk and systemic risk is magnified for highly connected firms. We obtain similar results using PAC contributions to federal candidates: the positive effect of political risk on systemic risk is amplified for firms occupying central positions within the PAC network. These results are in stark contrast to recent work on corporate political activity which attests an attenuating effect of CPA on firm-level political risk (Islam et al. 2022; Ho et al., 2024). Although these results are to be interpreted in a correlation sense and are not strictly causal, they do provide us a novel insight into the repercussions of corporate lobbying for systemic risk.

Our study speaks to two broad strands of literature, the first relating to firm-level political risk. The implications of political risk for corporate behaviour and performance outcomes have been extensively researched in the literature (Ahmad et al., 2023; Ahmed et al., 2022; Choi et al., 2022; Gorbatikov et al., 2019; Hassan et al., 2019; Huang et al., 2023a, 2023b). Relatively little attention has been observed for the systemic nature of political risk, barring recent studies by

[4] Lobbying firms are required to file lobby disclosure reports with the Secretary of the Senate's Office of Public Records (SOPR). CRP collects and standardizes data from SOPR and has made it available to the public on their website https://www.opensecrets.org/. The database also provides a list of 80 topics on which firms have lobbied. Details of their data collation methodology is available at https://www.opensecrets.org/federal-lobbying/methodology.

Chuliá et al. (2023) and Gad et al. (2023). We contribute to this literature by providing novel evidence on the association of firm level political risk with systemic risk. In doing so, we also contribute to the burgeoning literature on systemic importance of NFCs. The systemic risk literature has traditionally focused on the banking and financial services sector, owing in part to the far-reaching consequences of a banking system failure for the global economy. However, more recently, the literature has stressed that even NFCs can be systemically important because of their widespread connections to other NFCs and to the banking and financial services sector. While the systemic importance of NFCs has been examined from the lenses of trade and bank credit, we contribute by highlighting the importance of political risk and CPA for risk propagation. These results are of significance to regulators and policy makers who must constantly monitor signs of systemic stress to safeguard the financial system against economic and political shocks.

The paper proceeds as follows. We describe data and variables in section 2, followed by regression analyses in section 3. Channel effects are discussed in section 4, and section 5 offers concluding remarks.

2.Data and Variables

2.1. Data Sources

We utilize four data sources in our study. We extract quarterly firm fundamentals and daily stock price data from Compustat North America. The universe for our data comprises US listed firms with common stock issues traded on NYSE, NASDAQ, AMEX, or OTC markets. Data on board networks are constructed using director-level employment data from BoardEx. We source firm-level lobbying expenditures from the dataset prepared by the Center for Responsive Politics. The CRP standardizes data from lobbying reports filed by lobbying firms with the Secretary of the Senate's Office of Public Records. CRP's data is available for the public on their website https://www.opensecrets.org/. CRP also provides data on the bills lobbied by each firm, which they condense into a set of 80 broad issues. We use the lobbying issues data from CRP in our analysis of lobbying networks. Data on political contributions to federal candidates by business PACs are extracted from CRP. The CRP provides data on contributions made by PACs, beneficiary candidates, and party affiliation of each candidate within each 2-year election cycle. PAC and lobbying variables are merged with the main dataset using firm names, since CRP does not provide unique identifiers such as tickers or CUSIP[5]. Finally, data on quarterly firm-level political risk has been sourced from Hassan et al. (2019)[6]. Our sample spans the period 2002Q1-2021Q4 considering the availability of data on firm-level political risk. We restrict our sample to firms whose fiscal quarters coincide with calendar quarters. This is done to maintain congruence with the CRP lobbying dataset, which is at calendar-quarter level. After considering necessary stipulations on data (discussed appropriately in further sections), our baseline sample consists of 5,445 unique firms, which translates to 161,713 firm-quarters.

2.2. Variable Construction

2.2.1. Firm-level Political Risk

Hassan et al. (2019) constructed firm-level political risk measures by quantifying the proportion of time spent during earnings conference calls on topics of political nature. Specifically, they employ tools of computational linguistics to count the number of bigrams of political nature, in close proximity to words indicating risk, uncertainty, or their synonyms. To distinguish between political and non-political topics, they employ a training library of political text, and another for non-political text. The final measures of political risk indicate the share of conversation during earnings calls spent on political topics[7]. We scale the original Prisk variable by 100 in our regressions.

2.2.2. Systemic Risk

We employ ΔCoVaR as proposed by Adrian & Brunnermeier (2016) as the measure of systemic risk contribution of each firm. ΔCoVaR estimates the contribution of each firm's distress state to the distress of the financial system (market). Specifically, it measures the change in conditional value-at-risk (CoVaR) of the system when the firm moves from the normal (median) state to a distress state. Following prior literature on systemic risk (Adrian & Brunnermeier, 2016; Brunnermeier et al., 2020; Dungey et al., 2022), we define distress state of a

[5] CRP presents data by company name as on the date of lobbying disclosure report, whereas Compustat provides the most current company name as on datadate. Considering the fact that company names may change over the life of a firm, we first extract the list of historical company names for each firm from CRSP COMPHIST files. Then, we use fuzzy name matching to generate a set of matches between firm names in CRP and historical company legal name (HCONML) in Compustat. We finalize the matches through manual screening and websearches. A similar procedure is followed for merging PAC data.

[6] We are grateful to the authors of Hassan et al. (2019) for providing their measures of firm-level political risk publicly at https://www.firmlevelrisk.com/.

[7] For a detailed discussion of construction of the Prisk variable, we refer the reader to the original paper by Hassan et al. (2019).

firm as the event of its stock returns being in the worst 5% and 1% during the period (quarter). Thus, ΔCoVaR measures the change in value-at-risk of the financial system when the firm's value-at-risk moves from the median state to the 5% and 1% tail states. We follow Adrian and Brunnermeier (2016) and follow two steps to estimate ΔCoVaR. First, we run the following quantile regressions using weekly returns data:

$$X_{i,t} = \beta_{i1} + \beta_{i2} M_{t-1} + \varepsilon_{i,t} \quad (1)$$

$$X_{m,t} = \gamma_{system|i} + \beta_{system|i} X_{i,t} + \delta_{system|i} M_{t-1} + \varepsilon_{i,t} \quad (2)$$

Here, $X_{i,t}$ and $X_{m,t}$ are losses (returns multiplied by -1) on the firm $i's$ equity and on the market equity in week *t.* Following prior literature (Dungey et al., 2022), we employ the S&P 500 index as proxy for the market because it is widely followed as the benchmark stock index in the US[8]. M_{t-1} are a set of state variables designed to generate time variation in the joint distribution of firm and market losses. State variables include changes in the 3-month T-bill rate, change in term premium, change in credit spread, change in TED spread, weekly market return, and 22-day rolling standard deviation of market returns. Eq. (1) is estimated at three quantiles – 50% (median state), 95% and 99% (distress states). Eq. (2) is estimated at the two distress states (95% and 99%). Quantiles at 95% and 99% of losses translate to the worst 5% and 1% of returns. We extract the predicted values from eq. (1), which gives us the VaR of the firm at 50%, 5%, and 1%. The coefficient $\beta_{system|i}$ from Eq. (2) depicts the vulnerability of the system to distress at firm *i.* In the second stage, the weekly ΔCoVaR for each firm is estimated as follows:

$$\Delta CoVaR_{i,t,q} = \beta_{system|i,q} \left(VaR_{i,t,q} - VaR_{i,t,50\%} \right) \quad (3)$$

Here, q indicates the quantile considered as a distress state, which is 5% and 1% for us. Weekly stock returns are computed using daily stock prices sourced from the Compustat North America database. Following Varotto & Zhao (2018b), we only keep firms with at least 80% non-zero weekly stock returns over the entire period to alleviate concerns about illiquid stocks. We also eliminate remove observations with non-positive stock prices. We aggregate weekly ΔCoVaR at the quarterly level by taking the average of all weeks in the quarter. In addition to Adrian and Brunnermeier's (2016) systemic risk measure, we also estimate two additional measures of

[8] In robustness tests, we repeat our baseline analyses using a broader market index, the Russell 3000, and find results which are qualitatively similar.

delta CoVaR wherein Eq. (1) and Eq. (2) are estimated on a rolling basis using a three-year window (Anginer et al. 2018).

2.2.3. Control Variables

We employ a wide set of variables to control for traditional firm characteristics affecting systemic risk. These include firm size, which is the natural log of total assets; return on assets ROA, which is net profit scaled by total assets; leverage, which is the ratio of total debt to total assets; market-to-book, which is the ratio of equity market capitalization to book value of common equity; cash ratio, which is cash and cash equivalents scaled by total assets; accounts payables scaled by total assets; accounts receivables scaled by total assets; and asset tangibility, which is net property, plant, and equipment scaled by total assets. We also control for the individual firm's VaR to account for the possibility that firms which are inherently risky also contribute more to systemic risk. All accounting variables are matched to market-based variables by lagging a quarter, to preclude look-ahead bias (Andreou et al., 2021). In robustness tests, we control for economy-wide policy risk using economic policy uncertainty (EPU) index at the state of firm's headquarters (Baker et al., 2022). All firm-level variables are winsorized period-by-period at 1% and 99% level to minimize the effect of outliers.

2.2.4. Board Networks

Two firms are said to be connected if their boards share a common director in any given quarter. Following Amin et al. (2020), we only consider current employment connections in each quarter, as opposed to education or social connections. BoardEx provides detailed employment data for directors, including employment in listed and unlisted firms. We first extract current and past employment data for the comprehensive list of directors in our sample firms. Then, for each year-quarter, we identify board-level connections using the presence of common directors in that quarter. Board networks are separately constructed in each quarter. We employ three network centrality measures to estimate the connectedness of a firm within the board network. The first and most simple measure is *network degree*, which is the number of direct connections which a firm has to others in the network. Specifically, network degree is defined as follows:

$$nw\_degree_i = \sum_j x_{ij} \tag{4}$$

A possible limitation of network degree is that it only counts *direct* connections. It is more plausible that information flow within the network may occur through indirect connections as well. A firm may have few direct connections, but its influence as a potential information diffusion node in the network may be magnified if its direct connections are also well connected. In essence, one must consider both the number and quality of a firm's direct connections. To that end, we employ *eigenvector centrality* as the next measure of board connectivity. Eigenvector centrality puts appropriate weights on a firm's direct connections to account for their connectivity. Specifically, eigenvector centrality is defined as follows:

$$nw\_eigenvector_i = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij}\left(nw_{eigenvector}\right)_j \tag{5}$$

Finally, we also calculate *betweenness centrality,* which counts the number of instances where the firm falls on the shortest path between two other firms. Essentially, betweenness measures how influential a firm can be in bridging the information gap between other firms in the network. Conversely, it measures the potential of a firm to be an "information broker" between two other firms (Cheng et al., 2019). Betweenness centrality is defined formally as below:

$$nw\_betweenness_i = \sum_{j \neq k}^{i \neq j \neq k} {D_{i,jk}}\Big/{D_{jk}} \tag{6}$$

Here, $D_{i,jk}$ is the number of geodesics (shortest paths) between firms j and k, and D_{jk} is the total number of geodesics between j and k. To ensure comparability of network centrality measures in each quarter, we standardize all three measures to have a mean of 0 and standard deviation of 1.

2.2.5. Lobbying Variables

We construct two types of variables to study the impact of lobbying activity. The first set of variables are related to lobbying expenditures: (1) a dummy variable indicating whether a firm has incurred expenditures toward lobbying activity in a given quarter, and (2) the natural logarithm of one plus actual lobbying expenditures incurred in that quarter. The second set of variables are constructed using lobbying networks. The CRP provides a list of broad issues towards which a firm incurs lobbying expenditures in any given quarter. Using a procedure similar to the creation of board interlocking networks, for each quarter, we create lobbying networks by identifying common issues lobbied by firms. Thus, whereas in board networks the edges were formed by common directors, common lobby issues form the edges in the lobbying networks. These networks may offer two distinct perspectives on how firms are connected. First, to the extent that firms functioning along similar lines of business would be more inclined to lobby towards similar issues, lobbying networks may offer novel insights into how firms in the same business may be connected, beyond traditional channels such as trade and bank credit. Second, the lobbying data reveals that firms do lobby towards causes which may not directly relate to their line of operation. Ergo, the said network may reveal potential 'non-business' channels of connection among firms, even those which operate in different business lines. We estimate two network centrality measures for the lobbying networks: degree, and eigenvector. Both variables are standardized within each quarter to have a mean of zero and standard deviation of 1.

2.2.6. Corporate Political Contributions Data

Similar to lobbying variables, we construct variables to indicate PAC activity by corporates. To identify firms engaging in political contributions, we construct two variables: (1) a dummy variable to indicate whether a firm's PAC donated to federal candidates in the specific quarter; and (2) a variable as the natural logarithm of 1 plus actual contribution made by the PAC[9]. To demonstrate network effects, we construct, in each quarter, networks of firms connected through political contributions made to common federal candidates. Similar to lobby networks, PAC networks may reveal potential "non-business" connections between firms. We define a firm's influence within the network using two centrality scores: degree, and eigenvector. Both scores are standardized by quarter to ensure comparability across time.

3. Main Results

3.1. Descriptive Statistics

Panel A in Table 1 presents summary statistics of the main variables. The mean systemic risk measures at 95%ile are 1.59% and 1.78%, which is comparable to estimates provided in prior literature(Adrian & Brunnermeier, 2016; Brunnermeier et al., 2020), albeit slightly higher. Higher systemic risk in our sample may, in part, be attributed to the Covid-19 pandemic in 2020, a year which experienced unprecedented crashes across global stock markets. The average (median) firm has a political risk of 1.21 (0.64), although the standard deviation is much higher

[9] The CRP data on PAC contributions also report few instances of negative contributions, which are essentially contribution refunds. We replace these figures with zero as they effectively entail no contribution.

at 1.74. This indicates considerable heterogeneity in the distribution of political risk across firms. In Panel B, we observe a strong positive correlation between firm-level political risk and all four measures of systemic risk.

3.2. Baseline Model

Our empirical analysis begins by studying the relationship between firm-level political risk and systemic risk contribution. We employ the following regression model:

$$Y_{i,t} = \alpha_1 + \alpha_2 PRisk_{i,t} + \sum_k \beta_k X_{ki,t-1} + \delta_i + \theta_t + \varepsilon_{i,t} \tag{7}$$

Here, the dependent variable, $Y_{i,t}$, takes one each of the four systemic risk measures. The coefficient of interest is α_2, which indicates the association between political risk and systemic risk. We include firm fixed effects and calendar year dummies in all regressions to account for time and firm-invariant unobservable heterogeneity. Further, standard errors are clustered at firm-level. Our regressions control for a set of nine variables which may affect systemic risk. The results are presented in Table 2, columns 1-4. We find a strong positive association between firm-level political risk and systemic risk across all four models. The relationship of systemic risk with control variables is consistent with the related literature (Adrian & Brunnermeier, 2016; Caporin et al., 2023; Dungey et al., 2022). Larger firms contribute more to systemic risk, as do more profitable ones. Firms which extend greater trade credit (indicated by proportion of accounts receivables) contribute more to systemic risk, which is consistent with the literature on banking and financial services firms, where lenders are considered more systemically important. A negative shock to an important lender induces financing constraints on all other firms which rely on it for trade credit, thus hastening a systemic crisis. On the other hand, systemic risk appears to have a negative association with the level of firm indebtedness. Both leverage and trade credit (indicated by accounts receivables) exhibit negative coefficients, which are consistent across all specifications. This may appear counterintuitive, as one may expect firms holding more debt to contribute more to a market-wide crash. It is, however, more plausible that there are significant feedback effects between systemic risk and level of indebtedness. As Dungey et al. (2022) explains, the market may already be factoring in the systemic risk of a firm before granting any form of credit. In essence, this indicates that the market purposefully channels credit, both financial and trade-based, to firms which have a lower likelihood of contributing to a systemic event. This may explain why we consistently observe a negative coefficient on both leverage and trade credit ratios.

Although Hassan et al. (2019) reports that more than 90% of the political risk is idiosyncratic to the firm, one may still argue that firm-level political risk may be picking up the effects of a market-wide political shock. In fact, Hassan et al. (2019) finds that the time-averaged firm-level political risk is strongly correlated with economic policy uncertainty (EPU) index (Baker et al., 2016), having a significant correlation of 0.821. To ensure that our results are, in fact, being driven primarily by firm-specific political risk, and not by a common policy-related shock, we additionally control for economic policy uncertainty (EPU) at the state of a firm's headquarters. State-level EPU indices were constructed using related media coverage by Baker et al. (2022). The resulting coefficients, presented in columns 5-8 of Table 2, depict that state-level EPU indeed positively affects systemic risk. The positive association between firm-level political risk and systemic risk continues to hold, however, which supports our initial findings.

3.3. Robustness Tests

Our baseline regressions indicate that an increase in firm-level political risk is accompanied by a rise in systemic risk contribution. We now ensure that the baseline results remain consistent across a battery of robustness tests.

One may argue that systemic risk rises simply because of an increased overall risk perception, which may not necessarily be attributed to political sources. Hassan et al. (2019) also developed measures of non-political risk, which capture the proportion of earnings conference calls which were devoted to non-political topics. Following Hassan et al. (2019) and Chatjuthamard et al. (2021), we conduct a falsification exercise wherein we rerun our baseline models with non-political risk (NPrisk) as an additional control variable. To the extent that Prisk indeed captures risks of political nature, we expect to retain a positive coefficient even in the presence of NPrisk. The results, presented in Table 3, does attest to our expectations. The coefficients on Prisk remain positive and statistically significant across all specifications. This observation provides more confidence in the assertion that political risk, as opposed to other sources of risk, is additionally informative as a contributing factor to systemic risk.

Next, we differentiate between variance in the mean of political risk. Given that the measure of firm-level political risk is based on the perception and discussion of political topics during earnings calls, it is possible that such a discussion may be precipitated by specific negative political shocks to the firm. Firm management may respond more to the incidence of unfavorable political events, as opposed to favorable ones. Consequently, one needs to control for the variation in the mean of political shocks to arrive at more accurate estimates for political risk. This has been duly recognized by Hassan et al. (2019), who then develop estimates of political sentiment, which captures the nature of political conversation during earnings calls. Assuredly, they find that the correlation between firm-level political risk and political sentiment is significantly negative, which corroborates the above argument. In line with Hassan et al. (2019), we additionally control for political sentiment (Psentiment) in Table 4. We find that political sentiment is negatively associated with systemic risk, which is consistent with the supposition that incidence of positive political news reduces systemic risk contribution. More importantly, the coefficients on Prisk remain positive and significant, with only minor change in the magnitude. This provides an additional layer of robustness on our baseline findings.

Another concern with the baseline results is that the measures of firm-level political risk may persist across time. Unforeseen political events are rare; in fact, issues pertaining to policy-related uncertainty or political gridlock may sustain over multiple quarters or even years. Even after resolution of uncertainty, the aftereffects may linger. To control for the persistent nature of political risk, we follow Islam et al. (2022) and rerun the baseline models after additionally controlling for one lag of political risk. We do not expect lagged political risk to be statistically significant for two reasons. First, the contemporaneous political risk (Prisk) in our baseline models captures information from earnings calls which essentially pertain to the previous quarter. Second, most earnings conference calls take place within the first month of the quarter (Hassan et al. 2019). Assuming that markets are reasonably efficient, we expect information revealed during earnings calls to be absorbed within the same quarter itself. Consistent with these arguments, we find that lagged political risk is not significant (Table 5). Contemporaneous Prisk remains positive and significant, however, which encourages robustness of our results.

In our baseline models, we include firm fixed effects and calendar year dummies to control for unobserved heterogeneity which may be firm-invariant or time-invariant. However, evidence from extant literature indicates that certain industries may be more politically sensitive than others (Chuliá et al., 2023; Dungey et al., 2022; Islam et al., 2022). As an additional robustness check, we re-estimate the baseline models by using firm and industry-year fixed effects. We classify firms according to Fama-French 48 industries, based on their SIC codes. As observed in Table 6, the results continue to remain consistent under this alternate specification.

In our estimation of systemic risk measures, we employed the S&P 500 as a proxy for the market considering its importance as the representative stock index of the US market. The performance of the S&P 500 is considered a close approximator for the US economy as a whole, and has been used as a proxy for the market portfolio in the systemic risk literature (Dungey et al., 2022). A possible caveat with this approach is that the S&P 500 consists of the largest 500 stocks in the US based on market capitalization, which makes it a large-cap-only portfolio. Our sample, however, is a mix of large, mid, and small-cap firms. One may, thus, argue that our results may be sensitive to the choice of the market index. To alleviate such concerns, we redo our systemic risk estimation and baseline analysis by replacing the S&P 500 with a much broader market index, the Russell 3000. The Russell 3000 captures almost 98% of investable equity market in the US, including all large, mid, and small cap stocks[10]. Not only do our results remain qualitatively similar, but we also find negligible differences in the magnitude of coefficients on Prisk (Table 7). Accordingly, we conclude that our results are largely insensitive to the choice of market index.

Our primary focus in this study remains on political risk and its effect on systemic risk contribution. Keeping this in mind, we do not exclude banks or utility firms from our sample. Nonetheless, one of our major contributions is also to the budding literature on systemic importance of non-financial firms (NFCs). The systemic importance of banks is extensively studied, whereas NFCs have only recently attracted attention. Although the proportion of banks and utility firms in our sample is very low and unlikely to drive the results obtained so far, as an additional robustness for NFCs, we rerun baseline models after excluding these firms (Fama-French industry codes 31 and 44). As seen in Table 8, Prisk remains positive and significant, thus underscoring the systemic significance of non-financial firms.

3.4. Propensity Score Matching

The previous section illustrated the consistency of our baseline results across multiple specifications. A different cause of concern would arise if firms with high political risk differed significantly across firm-specific characteristics, from those with lower political risk. Although we control for a set of covariates in the baseline models, omitted variable bias may still affect the coefficients if the functional form is misspecified. To alleviate such concerns, we undertake propensity score matching. To do so, in each quarter, we first split the sample into four quartiles based on firm-specific political risk. Observations falling above the 75th percentile are classified as the treatment group (high political risk), and those below the 25th percentile as the control group (low political risk). We then estimate the probability of treatment using a logit

[10] Source: Russell 3000 Factsheet: https://www.lseg.com/en/ftse-russell/indices/russell-us#t-russell-3000

model, using all accounting-based controls. To match a treated observation with a control one in each quarter, we use caliper matching with a width of 0.05. To ensure that the final matched sample are similar across covariates, we re-estimate the logit model on the matched sample. As observed in Panel A of Table 9, none of the covariates are statistically significant in the matched sample, although this isn't the case for the full (unmatched) sample. Further, we conduct t-test to check for any statistical differences in mean values of the covariates between the treated and control groups for the matched sample. The results, shown in Panel A of Table 9, confirm that the matched sample are indeed similar across the included covariates. Finally, we re-run the baseline models on the matched sample (Panel B, Table 9). Our results remain qualitatively similar, affirming confidence in the baseline analysis.

3.5. Instrumental Variable Analysis

Given that the nature of our data is non-random, endogeneity is a valid concern. There may, for instance, be omitted variable bias arising because of inability to identify and include a variable which affects both Prisk and systemic risk simultaneously. Likewise, incorrect specification of functional form may also induce bias in the coefficients. In the preceding sections, we have employed a multitude of specifications, inclusion of fixed effects, and propensity score matching, to mitigate such concerns. As an additional step towards establishing the causal nature of the relationship, we conduct an instrumental variable analysis. Identification of a valid instrument remains a difficult task. Any valid instrument must satisfy two criteria. The first criterion requires that the instrument bear a significant partial correlation with the endogenous variable in question (relevance). The second criterion demands that the instrument be uncorrelated with the error term from the main regression (exclusion). In other words, the instrument must only affect the outcome through its effect on the endogenous variable, and must not, by itself, belong in the main regression. While the first criterion is easy to test within the regression framework, there does not exist any formal statistical test for the second one, which makes it difficult to identify and defend a suitable instrument.

We thus look into the existing literature on firm-level political risk to identify two instruments for Prisk. The first instrument we consider is the average firm-level political risk of all firms within the same industry as the focal firm, excluding the focal firm. The rationale behind this choice is that certain industries may be more politically sensitive than others, and a rise in industry-level political risk is expected to increase political risk of a firm belonging to the same industry. Moreover, there is no reason to expect that an industry-level rise in political risk should affect systemic risk through any channel other than through an increase in firm-level political risk. The second instrument we consider is the state-level average Prisk (Banerjee & Dutta, 2022; Chatjuthamard et al., 2021). States in the US have administrative freedom over most policy-making decisions, and may thus vary in terms of political exposure. Firms operating in politically-charges states may well be exposed to higher political risk. To ensure exogeneity, we calculate the instruments for each quarter and each firm, after excluding the focal firm from the calculation. We employ IV-2SLS as the estimation technique. In the first stage, Prisk is regressed on the instrument and the other control variables from the baseline model. In the second stage, we run regressions of systemic risk measures on instrumented Prisk and the other controlling covariates. The results are presented in Tables 10 and 11. As expected, we find that both instruments are positively and strongly correlated with Prisk in the first stage regressions. In addition, the Kleibergen Paap Wald rk statistics are highly significant, which ensures that the instruments are not weak, thus satisfying the relevance criteria. We also report weak instrument robust inference in the form of Anderson-Rubin Wald F-statistics. The P-values are all lower than 0.01, which attests validity of the excluded instruments. In the second stage regressions, we find that instrumented Prisk is positively associated with all four measures of systemic risk. The coefficients are all significant at the 1% level. We conclude that our baseline models remain strong in the presence of IV regressions.

4. Channel Effects

Having established a positive association between firm-level political risk and systemic risk contribution, we next focus our attention on channels which may facilitate risk propagation through the network. Network connections smoothen the flow of information across firms, thus potentially aggravating a firm's systemic risk contribution. To this effect, we analyse two types of networks: board interlocks, and corporate lobbying networks.

4.1. Board Interlocking Networks

Network effects of board interlocks through common directors have been studied extensively in the literature. In contrast to trade and credit-based connections which arise naturally due to business operations, board-level connections allow for linkages even across firms which are unrelated. Connections between boards enable information spillovers across firms, both public and private (Akbas et al., 2016; Cheng et al., 2019; Haunschild & Beckman, 1998; Larcker et al., 2013). While alleviation of information asymmetry may benefit firms through access to specialized knowledge (Amin et al., 2020; Chang & Wu, 2021; Dass et al., 2014), it could worsen the systemic risk potential of the firm by enabling flow of unfavourable information and triggering a fear-based contagion (Adasi Manu & Qi, 2023; Guo et al., 2024). Interlocked firms also exhibit similarity in corporate practices (Adasi Manu & Qi, 2023; Chiu et al., 2013; Fracassia, 2017). Incidence of financial distress at a well-connected firm may, thus, influence perceptions of similar weakness at their connections, potentially exacerbating contagion effects. Drawing from these arguments, we expect board connectivity to amplify the systemic risk contribution of firms with high political risk. We construct three network centrality measures to approximate board connectivity of firms. The measures are computed from networks constructed in each quarter. In regressions, we standardize each measure by quarter to ensure comparability. The simplest measure, degree centrality, simply counts the number of direct links between boards. To also account for the possible information spillovers through indirect connections, we compute eigenvector centrality, which assigns appropriate weights commensurate with the number of indirect links. Finally, we measure the importance of a firm being an 'information broker' between two other firms through the betweenness centrality[11]. Descriptive statistics for centrality measures are given in Table 12, Panel A. The mean firm is connected to approximately four other firms through common board directors. The maximum number of direct connections is 51. As expected, the centrality measures are also highly correlated.

To visualize the distribution of board connectivity across varying levels of political risk, in each quarter, we first classify firms into quartiles based on their level of political risk. We then compute descriptive statistics of the three board network centrality measures by quartile of political risk. The mean and standard deviation of centrality measures by quartile of Prisk are presented in Table 12, Panel B. Network connectivity is found to be higher for firms with high political risk. The t-test for difference of means (assuming unequal variances) in network centrality for firms at the bottom and top quartiles is significantly negative across all three centrality measures. This may indicate the importance of board connectedness as a potential channel through which political risk affects systemic risk. We explore this supposition formally through a regression specification of the following form:

$$Y_{i,t} = \alpha_1 + \alpha_2 PRisk_{i,t} + \alpha_3 Centrality_{i,t} + \alpha_4\left(PRisk_{i,t} \times Centrality_{i,t}\right) + \sum_k \beta_k X_{ki,t-1} + \delta_i + \theta_t + \varepsilon_{i,t} \qquad (8)$$

[11] Detailed computations are described in section 2.2.4.

Centrality takes each of the three network centrality measures – degree, eigenvector, and betweenness. To the extent that our supposition holds true, we expect α_4 to be positive. We include the same set of control variables as in the baseline model.

Table 13 presents the coefficient estimates from the estimation of eq. (8). The dependent variable are systemic risk measures at 95% and 99% respectively. Two observations are notable at this stage. First, the coefficient on Prisk remains positive and significant, which is consistent with our analysis thus far. Second, and more interestingly, we find that the interaction of Prisk with all three centrality measures are positive and statistically significant. Thus, while higher political risk does associate with greater systemic risk contribution, the effect is amplified for firms which occupy central positions within the board network. In essence, it highlights the systemic importance of politically exposed firms at the core of the board interlock network.

4.2. Corporate Lobbying Activity

One of the mainstream avenues by which firms actively attempt to influence government policy is through lobbying. Increasingly over the past two decades, US firms have expensed corporate cash towards lobbying efforts. Per our data, 31% of our firms have lobbied in 2021, with an average expenditure of $98,759, the maximum being $5,320,000. According to the stewardship theory, lobbying as a strategy allows firms to keep abreast of developments in government policy, especially regulation affecting business conditions. Moreover, while a single firm may have negligible influence in policy matters, lobbying by a cluster of firms has the potential to mould policy outcomes in their favour. Evidence to this effect has been documented by Alexander et al. (2009) and Markussen & Svendsen (2005), among others. For a firm which has considerable exposure to political risk, lobbying may also help manage such risk by bridging information asymmetry. Indeed, as Hassan et al. (2019) finds, an increase in firm-level political risk is positively associated with an increase in lobbying expenditure in the succeeding quarter. The agency view, however, argues that lobbying may be detrimental to the firm if firm management diverts corporate resources at the expense of shareholder value (Unsal et al., 2016). Whether or not lobbying benefits firms would ultimately depend on a trade-off between these two opposing forces. Against this backdrop, we study a different aspect of lobbying: its potential influence on systemic risk.

Firms lobby for a broad range of issues. While one would expect that firms lobby on matters of direct importance to their business, data from CRP reveals that firms do lobby for generic issues which may affect their business indirectly. Thus, firms operating in otherwise unrelated business lines may be connected if they lobby extensively toward the same cause. As such, this gives rise to a "lobbying network", where firms are connected through common lobby issues. Firms occupying central positions within this network are those which lobby toward multiple issues. The implications of this for systemic risk is, ex ante, unclear. On one hand, if the purpose of lobbying is to manage political risk, lobbying activity could mitigate such risk and consequently, reduce systemic risk exposure. Successful lobbying could also help influence policy-making at the government level and increase the likelihood of a bailout, which may further reduce systemic risk perception. On the other hand, however, lobbying activity could strengthen the political network even further. Firms could become connected simply because they stand to benefit from the same lobbying issue. Firms which have incurred heavy expenditures toward lobbying stand to be affected disproportionately higher from an unsuccessful lobby. This negative shock could propagate through their connections, giving rise to a systemic event. Lobbying may also expose firms to being "systemic as a herd" (Adrian and Brunnermeier, 2016) if an entire cluster of firms are affected by a shock arising out of a common lobby issue.

We empirically investigate these arguments using lobbying data from CRP. We examine both the tenets of lobbying activity, as well as their network effects. Table 14, Panel A broadly describes the corporate lobbying scenario. Out of our sample firm-quarters, 28.35% involve lobbying activity. Across the full sample, average quarterly lobbying expenditure is $91,000. The standard deviation is much higher at $384,386, which indicates considerable variation in lobbying intensity across firms. Average quarterly lobbying in 2021 Q4 was $104,305, compared to $55942 in 2002 Q1. Among lobbying firms exclusively, average quarterly expenditure is $320,978. On average, firms lobby for more than 1 issue, with a standard deviation of almost 3. This figure equals 1.41 in 2021 Q4, a rise from 1.36 a decade earlier (2012 Q4). Among lobbying firms exclusively, the mean number of issues is 4.31 overall, 4.35 in 2021 Q4, and 4.24 a decade earlier. The maximum lobbying expenditure in our sample is $19.09 million by PG&E Corp in 2008 Q3. With respect to network effects, the average degree centrality stands at 99, which means that the average firm is connected to 99 others via common lobby issues. This figure is 125 for the last quarter of 2021, a massive rise from just 69 in the same quarter of 2002. The figures demonstrate not just the pervasive rise in lobbying activity, but the considerable heterogeneity in intensity. In Panel B, Table 14, we summarize lobbying variables by quartile of Prisk. As expected, and consistent with Hassan et al. (2019), we find the mean lobbying expenditure to increase with each quartile, as do the number of issues. Network connectivity, too, is highest for firms at the top quartile of Prisk. While these findings are consistent with politically risky firms engaging in more lobbying activity, it also raises concerns that systemic risk contribution may be magnified for these firms.

We demonstrate network effects by graphically visualizing the lobby network for the last quarter of 2012. We identified a total of 661 firms which lobbied in the last quarter of 2012. Fig.1, Panel A is the network plot for all lobbying firms. The nodes represent individual firms, whereas the edges (connections) arise from common lobby issues. As observed, the network is extremely dense, with multiple connections across firms. Network connections across industries is better illustrated in the network plot on Panel B, Fig. 1. Here, we construct the network using only the largest firm (by total assets) in each of the Fama-French 48 industries. As is evident, barring six firms, firms from 42 industries are connected in a dense network structure. This supports our previous arguments and encourages formal analysis in the subsequent section.

We formally investigate these arguments using a regression framework of the following form:

$$Y_{i,t} = \alpha_1 + \alpha_2 PRisk_{i,t} + \alpha_3 Lobby\_Variable_{i,t-1} + \alpha_4 (PRisk_{i,t} \times Lobby\_Variable_{i,t-1}) + \sum_k \beta_k X_{ki,t-1} + \delta_i + \theta_t + \varepsilon_{i,t} \quad (9)$$

In eq. (8) above, Lobby_Variable takes one of the lobbying indicators at each turn. The results are presented in Table 15. In Panel A, columns 1-2, we use an indicator variable for whether a firm undertakes lobbying activity in the immediately preceding quarter or not. We used one quarter lagged lobbying indicator here because, in contrast to Prisk which is revealed at the beginning of the quarter, lobbying activity is more likely to be spread out over the three months in the quarter and reported only in the succeeding month. In columns 2-4, the lobbying variable used is the natural logarithm of lobbying expenses plus 1. This variable, too, is lagged by one quarter. We find that the coefficients on the interaction terms are positive and significant, which indicates that greater lobbying activity has a magnifying effect on the association between political risk and systemic risk. Further, in Panel B, we use the number of issues lobbied by the firm in the preceding quarter as the lobbying variable. The interaction effect is again positive and significant, with the only exception being the systemic risk at 99% level. In Panel C, we study the effects of lobbying networks. Prisk is interacted with the two lobbying network variables – degree and eigenvector centrality. Consistent with our suppositions, we find that the interaction effects are significant and positive when the dependent variable is systemic risk at 95%. Hence, while firms do undertake lobbying as a strategy to manage their political exposure, our results suggest that increase in lobbying may actually worsen risk propagation from politically risky firms. We acknowledge that these results do not establish causality; however, it does highlight the importance of corporate lobbying on systemic importance of politically risky firms.

4.3. PAC Contributions

Historically, political contributions have been viewed as a mechanism to establish and maintain connections with politicians (Correia, 2014). Although PAC contributions are employee-based donations and do not entail a run on corporate resources, firms and their management have considerable influence over the decision to establish a PAC. Cultivating relationships with political actors appear to reap significant benefits for contributing firms. PAC contributions have been associated with preferential access to external finance (Claessens et al., 2008), greater likelihood of bailouts under distress (Blau et al., 2013), and higher takeover premiums (Croci et al., 2017). Correia (2014) finds that firms with connections to politicians face lower probability of enforcement action and smaller penalties by the Securities and Exchange Commission (SEC). Akey (2015) finds that in the aftermath of a US congressional election, firms which donated to winning candidates experienced significant abnormal stock returns and post-election sales, relative to firms which donated to losing candidates. On the other hand, Fowler et al. (2020) finds no evidence of political favours enjoyed by firms engaged in political activity. While the supposed benefits, or lack thereof, of corporate PAC contributions remains contestable, a more convincing argument put forth in recent literature is that PAC activity shields firms from political uncertainties. Indeed, Bradley et al. (2016) document that political contributions alleviate the negative effects of policy uncertainty on borrowing costs. In their seminal work on firm-level political risk, Hassan et al. (2019) find that firms incur greater PAC contributions in the face of high political risk, which is suggestive of firms actively cultivating political connections to manage their political risk.

Whether corporate PAC activity affects systemic risk contribution is ex ante unclear. To the extent that PAC contributions are effective in managing political risk of individual firms, systemic risk may well be lower. However, PAC contributions also bring firms closer within the political network, in effect intensifying their exposure to common political shocks. Evidence of firms actively building political networks is documented by Akey (2015), who find that firms undertake coordinated decisions to build and maintain political relationships. In essence, systemic risk contributions may be exacerbated in the presence of corporate PAC activity.

We empirically examine the relevance of these arguments using data on corporate PAC contributions to federal candidates. In our sample, approximately 17.3% of firm-quarters exhibit positive PAC contributions (Table 16, Panel A). The mean quarterly contribution among donating firms is approximately \$31,000, with the maximum being \$7,33,600 by Honeywell International Inc PAC in 2010 Q3. The average corporate PAC contributes to 16 federal candidates in a quarter, the maximum being 294 by Lockheed Martin Corp PAC in 2015 Q2. Turning to network effects, we find that the mean degree centrality is about 25, which means that the average firm is connected to 25 others through contributions made to common federal candidates. Considering active contributors exclusively, this figure stands at 141. In Table 16, Panel B, we summarize this data by quartile of political risk. Consistent with Hassan et al. (2019), we find the intensity of PAC contributions to increase with political risk. The difference between firms in the top and bottom quartile is statistically significant across all measures of PAC activity.

The PAC network is visualized in Fig.2. Panel A includes all contributing PACs in 2012 Q4, whereas in Panel B, we reconstruct the network to demonstrate connections between the largest firm (by total assets) in each of the 48 Fama-French industries. The density of these networks encourages our subsequent analysis.

We employ regression specifications of the following form with firm fixed effects and calendar year dummies:

$$Y_{i,t} = \alpha_1 + \alpha_2 PRisk_{i,t} + \alpha_3 PAC\_Variable_{i,t-1} + \alpha_4\left(PRisk_{i,t} \times PAC\_Variable_{i,t-1}\right) + \sum_k \beta_k X_{ki,t-1} + \delta_i + \theta_t + \varepsilon_{i,t} \quad (10)$$

PAC_Variable takes one each of four variables which define PAC activity. The first, *PAC_Contributor,* is an indicator variable for firms with positive PAC contributions. Next, we use the natural logarithm of one plus actual PAC contribution made in each quarter. The third and fourth variables measure degree and eigenvector centrality, respectively, of the PAC networks constructed using contributions to common federal candidates. All PAC variables are lagged by one quarter. The results are presented in Table 17. We find that the interaction terms are positive and significant when using the PAC dummy and amount of contribution (Panel A), which suggests that higher contributions in the face of high political risk might exacerbate risk contagion. Looking at network effects (Panel B), we find that the interaction terms are positive across all measures, and statistically significant in three out of four models. Prisk continues to remain positively associated with systemic risk. Interestingly, in columns 5 and 7, where the systemic risk was estimated at 95% level using a 2-year rolling period, all three coefficients (Prisk, PAC variable, and their interaction) are positive and significant, which is suggestive of corporate political activity being detrimental to risk contagion.

5. Conclusion

Extant scholarship on firm-level political risk has focused almost exclusively on firm-level corporate behaviour and outcomes, such as investment, financing preferences, and pay-out decisions. Little attention is observed on the rise of the 'political network' which may connect firms through non-traditional, non-business channels, potentially facilitating risk propagation. Two recent papers find evidence to this effect. Chulia et al. (2023) use network tools to demonstrate development of the firm-level political risk network, whereas Gad et al. (2023) goes one step further to document transmission of political risk through private lending relationships. We add a novel perspective to this literature by examining whether firm-level political risk exacerbates risk transmission through the network. Using systemic risk measures as the indicator of risk transmission, we document a positive association between firm-level political risk and systemic risk contribution. We confirm consistency of the results through a battery of robustness tests, as well as propensity score matching and an instrumental variable analysis for alleviating endogeneity concerns. Having done so, we study two sources of network connections which may amplify this association. We first examine board interlock networks. Drawing from the literature on board interlocks which evidence information transmission and diffusion of corporate practices through shared directors, we study whether board connections affect the association between firm-level political risk and systemic risk. We find the association to be magnified for firms at central positions in the board interlock network. Finally, we study corporate political activity. Hassan et al. (2019) finds that firms undertake enhanced lobbying and political contributions in response to high political risk. As such, lobbying may be a strategy aimed at managing their high political exposure. On the flip side, lobbying may make a firm more influential in the systemic risk network if they expend huge corporate resources towards lobbying. Moreover, lobbying across multiple issues may give rise to a 'lobbying network', where firms lobbying toward similar issues may be vulnerable as a whole to negative shocks. Using lobbying data from CRP, we find that lobbying activity has a magnifying effect on the association between firm-level political risk and systemic risk. Moreover, similar to the results for board networks, the political risk-systemic risk relationship is heightened for firms which are more connected within the lobbying network. We observe similar results using political campaign contributions.

The literature on systemic risk has only recently awarded attention to non-financial corporations (NFCs). It is crucial to study the systemic importance of NFCs, considering the extensive network they exhibit through trade credit and corporate debt. Our study provides a novel perspective by highlighting political risk as a contributing factor in systemic risk. Against the backdrop of rising corporate political activity, monitoring these firms is of paramount importance for firm management, investors, and policymakers alike.

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Table 1: Description of Data

Panel A: Summary Statistics

	N	Mean	Median	SD	25th Percentile	75th Percentile
$\Delta CoVaR_{95\%}$	161,713	1.59%	1.50%	0.85%	1.05%	1.98%
$\Delta CoVaR_{99\%}$	161,713	2.76%	2.60%	1.57%	1.75%	3.54%
$\Delta CoVaR_{95\%,rolling}$	161,713	1.78%	1.55%	1.26%	0.92%	2.37%
$\Delta CoVaR_{99\%,rolling}$	161,713	2.67%	2.23%	2.17%	1.21%	3.61%
Prisk	161,713	1.21	0.64	1.74	0.20	1.48
Size	161,713	7.08	7.06	2.03	5.66	8.45
ROA	161,713	-0.00	0.01	0.06	-0.00	0.02
Leverage	161,713	0.25	0.21	0.23	0.05	0.38
Cash	161,713	0.19	0.10	0.22	0.03	0.27
Market-to-Book	161,713	3.13	2.06	6.25	1.19	3.67
A/c Payables	161,713	0.12	0.05	0.18	0.02	0.11
A/c Receivables	161,713	0.17	0.12	0.17	0.05	0.20
Tangibility	161,713	0.23	0.13	0.24	0.05	0.34

Panel B: Correlation Matrix

	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$	Prisk
$\Delta CoVaR_{95\%}$	1				
$\Delta CoVaR_{99\%}$	0.7828***	1			
$\Delta CoVaR_{95\%,rolling}$	0.6026***	0.4826***	1		
$\Delta CoVaR_{99\%,rolling}$	0.4506***	0.4141***	0.7403***	1	
Prisk	0.0269***	0.0180***	0.0545***	0.0555***	1

Note: This table describes the main variables over 161,713 firm-quarters. Variable construction is described in section 2. All variables have been winsorized at 1 and 99 percentiles to minimize the effect of outliers. Panel A presents summary statistics and Panel B presents Pearson correlation between systemic risk measures and firm-level political risk. *, **, and *** indicates statistical significance at 10%, 5%, and 1% respectively.

Table 2: Baseline Results

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%,rolling}$	(4) $\Delta CoVaR_{99\%,rolling}$	(5) $\Delta CoVaR_{95\%}$	(6) $\Delta CoVaR_{99\%}$	(7) $\Delta CoVaR_{95\%,rolling}$	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk	0.0041***	0.0070***	0.0053***	0.0084***	0.0033***	0.0055***	0.0038**	0.0067**
	(0.0007)	(0.0013)	(0.0017)	(0.0031)	(0.0008)	(0.0014)	(0.0018)	(0.0033)
Size	-0.0039	0.0060	0.2859***	0.4324***	-0.0041	0.0087	0.2865***	0.4301***
	(0.0034)	(0.0063)	(0.0139)	(0.0253)	(0.0035)	(0.0065)	(0.0146)	(0.0266)
ROA	0.1457***	0.0318	0.4729***	0.5469***	0.1761***	0.0835	0.4939***	0.5430***
	(0.0335)	(0.0570)	(0.0845)	(0.1544)	(0.0351)	(0.0593)	(0.0887)	(0.1611)
Leverage	-0.0000	0.0278	-0.6075***	-0.8700***	-0.0037	0.0119	-0.6216***	-0.8911***
	(0.0130)	(0.0245)	(0.0472)	(0.0835)	(0.0135)	(0.0252)	(0.0489)	(0.0862)
Cash	0.0291*	0.0520*	-0.0281	-0.1504	0.0307*	0.0654**	-0.0436	-0.1925*
	(0.0159)	(0.0291)	(0.0565)	(0.1014)	(0.0163)	(0.0301)	(0.0593)	(0.1055)
Market-to-Book	-0.0000	-0.0004	0.0020***	0.0013	-0.0000	-0.0004	0.0016**	0.0009
	(0.0002)	(0.0004)	(0.0006)	(0.0013)	(0.0002)	(0.0004)	(0.0006)	(0.0013)
A/c Payables	-0.1736***	-0.2478***	-0.3463***	-0.5697***	-0.1844***	-0.2432***	-0.3621***	-0.6042***
	(0.0455)	(0.0787)	(0.1212)	(0.2010)	(0.0468)	(0.0814)	(0.1313)	(0.2194)
A/c Receivables	0.1031***	0.1756***	0.1355	0.4943**	0.1103***	0.1790**	0.1557	0.5314***
	(0.0332)	(0.0665)	(0.1093)	(0.1961)	(0.0347)	(0.0695)	(0.1143)	(0.2046)
Tangibility	-0.0929***	-0.1088**	-0.2479**	-0.3002*	-0.0930***	-0.1084**	-0.2340**	-0.3378**
	(0.0248)	(0.0457)	(0.0962)	(0.1649)	(0.0257)	(0.0467)	(0.1013)	(0.1698)
$VaR_{95\%}$	0.1168***				0.1157***			
	(0.0019)				(0.0020)			
$VaR_{99\%}$		0.1003***				0.0997***		
		(0.0019)				(0.0020)		
$VaR_{95\%,rolling}$			0.1018***				0.1010***	
			(0.0018)				(0.0018)	
$VaR_{99\%,rolling}$				0.1037***				0.1031***
				(0.0017)				(0.0018)
State-level EPU					0.0005***	0.0009***	0.0008***	0.0008***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	161,713	161,713	161,713	161,713	149,525	149,525	149,525	149,525
R-squared	0.6801	0.6412	0.5300	0.5099	0.6837	0.6467	0.5325	0.5091
Number of Firms	5,445	5,445	5,445	5,445	4,906	4,906	4,906	4,906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7). The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Robustness – with non-political risk

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%,rolling}$	(4) $\Delta CoVaR_{99\%,rolling}$	(5) $\Delta CoVaR_{95\%}$	(6) $\Delta CoVaR_{99\%}$	(7) $\Delta CoVaR_{95\%,rolling}$	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk	0.0034***	0.0059***	0.0048***	0.0088***	0.0027***	0.0045***	0.0036*	0.0073**
	(0.0007)	(0.0013)	(0.0018)	(0.0032)	(0.0008)	(0.0014)	(0.0018)	(0.0033)
NPRisk	0.0000***	0.0000***	0.0000	-0.0000	0.0000***	0.0000***	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size	-0.0037	0.0064	0.2861***	0.4323***	-0.0039	0.0090	0.2866***	0.4299***
	(0.0034)	(0.0063)	(0.0139)	(0.0253)	(0.0035)	(0.0065)	(0.0146)	(0.0266)
ROA	0.1473***	0.0346	0.4739***	0.5461***	0.1772***	0.0855	0.4943***	0.5419***
	(0.0335)	(0.0570)	(0.0845)	(0.1544)	(0.0351)	(0.0593)	(0.0887)	(0.1611)
Leverage	-0.0002	0.0276	-0.6075***	-0.8700***	-0.0038	0.0116	-0.6216***	-0.8910***
	(0.0130)	(0.0245)	(0.0472)	(0.0835)	(0.0134)	(0.0252)	(0.0489)	(0.0862)
Market-to-Book	-0.0000	-0.0004	0.0020***	0.0013	-0.0000	-0.0004	0.0016**	0.0008
	(0.0002)	(0.0004)	(0.0006)	(0.0013)	(0.0002)	(0.0004)	(0.0006)	(0.0013)
Cash	0.0291*	0.0519*	-0.0281	-0.1504	0.0307*	0.0655**	-0.0436	-0.1925*
	(0.0159)	(0.0291)	(0.0566)	(0.1014)	(0.0163)	(0.0301)	(0.0593)	(0.1055)
A/c Payables	-0.1731***	-0.2471***	-0.3458***	-0.5700***	-0.1841***	-0.2426***	-0.3619***	-0.6046***
	(0.0454)	(0.0786)	(0.1212)	(0.2010)	(0.0467)	(0.0813)	(0.1313)	(0.2193)
A/c Receivables	0.1034***	0.1761***	0.1357	0.4941**	0.1107***	0.1796***	0.1559	0.5310***
	(0.0332)	(0.0665)	(0.1093)	(0.1961)	(0.0347)	(0.0696)	(0.1143)	(0.2046)
Tangibility	-0.0923***	-0.1079**	-0.2474**	-0.3005*	-0.0923***	-0.1074**	-0.2337**	-0.3385**
	(0.0248)	(0.0458)	(0.0962)	(0.1648)	(0.0256)	(0.0466)	(0.1013)	(0.1698)
$VaR_{95\%}$	0.1168***				0.1156***			
	(0.0019)				(0.0020)			
$VaR_{99\%}$		0.1003***				0.0997***		
		(0.0019)				(0.0020)		
$VaR_{95\%,rolling}$			0.1018***				0.1010***	
			(0.0018)				(0.0018)	
$VaR_{99\%,rolling}$				0.1037***				0.1031***
				(0.0017)				(0.0018)
State-level EPU					0.0005***	0.0009***	0.0008***	0.0008***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	161,713	161,713	161,713	161,713	149,525	149,525	149,525	149,525
R-squared	0.6801	0.6413	0.5300	0.5099	0.6837	0.6468	0.5325	0.5091
Number of Firms	5,445	5,445	5,445	5,445	4,906	4,906	4,906	4,906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7) with non-political risk (NPrisk) as an additional control variable. The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Robustness – with political sentiment

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%,rolling}$	(4) $\Delta CoVaR_{99\%,rolling}$	(5) $\Delta CoVaR_{95\%}$	(6) $\Delta CoVaR_{99\%}$	(7) $\Delta CoVaR_{95\%,rolling}$	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk	0.0036***	0.0061***	0.0049***	0.0077**	0.0029***	0.0047***	0.0036**	0.0061*
	(0.0007)	(0.0013)	(0.0017)	(0.0031)	(0.0008)	(0.0013)	(0.0018)	(0.0033)
PSentiment	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000**	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size	-0.0048	0.0044	0.2852***	0.4311***	-0.0048	0.0073	0.2860***	0.4291***
	(0.0034)	(0.0063)	(0.0139)	(0.0253)	(0.0035)	(0.0065)	(0.0145)	(0.0266)
ROA	0.1608***	0.0591	0.4840***	0.5661***	0.1879***	0.1043*	0.5002***	0.5571***
	(0.0335)	(0.0569)	(0.0848)	(0.1546)	(0.0351)	(0.0592)	(0.0890)	(0.1613)
Leverage	-0.0003	0.0272	-0.6073***	-0.8698***	-0.0039	0.0114	-0.6215***	-0.8909***
	(0.0129)	(0.0245)	(0.0472)	(0.0835)	(0.0134)	(0.0252)	(0.0488)	(0.0862)
Market-to-Book	-0.0000	-0.0003	0.0021***	0.0013	0.0000	-0.0003	0.0016**	0.0009
	(0.0002)	(0.0004)	(0.0006)	(0.0013)	(0.0002)	(0.0004)	(0.0006)	(0.0013)
Cash	0.0289*	0.0515*	-0.0281	-0.1505	0.0303*	0.0649**	-0.0437	-0.1927*
	(0.0159)	(0.0291)	(0.0565)	(0.1014)	(0.0163)	(0.0300)	(0.0593)	(0.1055)
A/c Payables	-0.1730***	-0.2468***	-0.3454***	-0.5684***	-0.1838***	-0.2422***	-0.3615***	-0.6029***
	(0.0454)	(0.0785)	(0.1212)	(0.2008)	(0.0466)	(0.0812)	(0.1312)	(0.2192)
A/c Receivables	0.1019***	0.1733***	0.1345	0.4927**	0.1098***	0.1780**	0.1554	0.5308***
	(0.0333)	(0.0665)	(0.1093)	(0.1959)	(0.0347)	(0.0695)	(0.1143)	(0.2044)
Tangibility	-0.0929***	-0.1091**	-0.2477**	-0.3002*	-0.0931***	-0.1088**	-0.2339**	-0.3379**
	(0.0248)	(0.0457)	(0.0962)	(0.1648)	(0.0256)	(0.0466)	(0.1013)	(0.1698)
$VaR_{95\%}$	0.1166***				0.1155***			
	(0.0019)				(0.0020)			
$VaR_{99\%}$		0.1001***				0.0996***		
		(0.0019)				(0.0020)		
$VaR_{95\%,rolling}$			0.1016***				0.1009***	
			(0.0018)				(0.0018)	
$VaR_{99\%,rolling}$				0.1036***				0.1030***
				(0.0017)				(0.0018)
State-level EPU					0.0005***	0.0009***	0.0008***	0.0008***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	161,713	161,713	161,713	161,713	149,525	149,525	149,525	149,525
R-squared	0.6805	0.6417	0.5301	0.5100	0.6840	0.6471	0.5325	0.5091
Number of Firms	5,445	5,445	5,445	5,445	4,906	4,906	4,906	4,906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7) with political sentiment (PSentiment) as an additional control variable. The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Robustness – with lagged political risk

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%,rolling}$	(4) $\Delta CoVaR_{99\%,rolling}$	(5) $\Delta CoVaR_{95\%}$	(6) $\Delta CoVaR_{99\%}$	(7) $\Delta CoVaR_{95\%,rolling}$	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk	0.0038***	0.0069***	0.0052***	0.0074**	0.0030***	0.0052***	0.0038**	0.0057*
	(0.0007)	(0.0012)	(0.0016)	(0.0029)	(0.0007)	(0.0013)	(0.0017)	(0.0030)
Lagged Prisk	-0.0000	-0.0005	0.0010	0.0030	-0.0000	-0.0006	0.0009	0.0027
	(0.0006)	(0.0012)	(0.0016)	(0.0029)	(0.0007)	(0.0012)	(0.0016)	(0.0030)
Size	-0.0025	0.0083	0.2909***	0.4375***	-0.0028	0.0105	0.2914***	0.4345***
	(0.0035)	(0.0065)	(0.0145)	(0.0262)	(0.0036)	(0.0067)	(0.0152)	(0.0275)
ROA	0.1336***	0.0154	0.4567***	0.4860***	0.1654***	0.0743	0.4775***	0.4944***
	(0.0361)	(0.0618)	(0.0898)	(0.1610)	(0.0378)	(0.0641)	(0.0943)	(0.1678)
Leverage	0.0003	0.0313	-0.6256***	-0.8983***	-0.0020	0.0185	-0.6398***	-0.9176***
	(0.0134)	(0.0256)	(0.0496)	(0.0866)	(0.0139)	(0.0263)	(0.0514)	(0.0894)
Market-to-Book	-0.0001	-0.0005	0.0018***	0.0010	-0.0001	-0.0006	0.0014**	0.0005
	(0.0002)	(0.0004)	(0.0007)	(0.0013)	(0.0002)	(0.0004)	(0.0007)	(0.0014)
Cash	0.0342**	0.0667**	-0.0299	-0.1467	0.0373**	0.0799***	-0.0410	-0.1833*
	(0.0164)	(0.0300)	(0.0594)	(0.1049)	(0.0168)	(0.0309)	(0.0623)	(0.1090)
A/c Payables	-0.1844***	-0.2562***	-0.3388***	-0.5043**	-0.1953***	-0.2574***	-0.3522**	-0.5324**
	(0.0486)	(0.0822)	(0.1272)	(0.2121)	(0.0495)	(0.0840)	(0.1381)	(0.2328)
A/c Receivables	0.1061***	0.1785**	0.1323	0.4210**	0.1132***	0.1820**	0.1518	0.4554**
	(0.0359)	(0.0710)	(0.1157)	(0.2045)	(0.0375)	(0.0742)	(0.1207)	(0.2128)
Tangibility	-0.0971***	-0.1084**	-0.2822***	-0.3649**	-0.0958***	-0.1041**	-0.2640**	-0.4009**
	(0.0259)	(0.0475)	(0.1000)	(0.1683)	(0.0267)	(0.0483)	(0.1052)	(0.1735)
$VaR_{95\%}$	0.1203***				0.1192***			
	(0.0019)				(0.0020)			
$VaR_{99\%}$		0.1032***				0.1025***		
		(0.0020)				(0.0021)		
$VaR_{95\%,rolling}$			0.1051***				0.1043***	
			(0.0018)				(0.0019)	
$VaR_{99\%,rolling}$				0.1060***				0.1054***
				(0.0018)				(0.0019)
State-level EPU					0.0005***	0.0009***	0.0008***	0.0008***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	151,873	151,873	151,873	151,873	140,595	140,595	140,595	140,595
R-squared	0.6917	0.6516	0.5389	0.5174	0.6954	0.6572	0.5416	0.5168
Number of Firms	5,174	5,174	5,174	5,174	4,667	4,667	4,667	4,667
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7) with one-quarter lagged Prisk as an additional control variable. The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Robustness – with industry-year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0034***	0.0058***	0.0040**	0.0069**	0.0025***	0.0041***	0.0028	0.0058*
	(0.0007)	(0.0012)	(0.0016)	(0.0030)	(0.0007)	(0.0013)	(0.0017)	(0.0032)
Size	-0.0021	0.0058	0.2820***	0.4353***	-0.0017	0.0086	0.2809***	0.4312***
	(0.0033)	(0.0063)	(0.0136)	(0.0249)	(0.0034)	(0.0065)	(0.0142)	(0.0262)
ROA	0.1469***	0.0457	0.4409***	0.4613***	0.1790***	0.0994*	0.4887***	0.4826***
	(0.0315)	(0.0555)	(0.0810)	(0.1496)	(0.0330)	(0.0578)	(0.0850)	(0.1561)
Leverage	-0.0150	0.0080	-0.5446***	-0.7731***	-0.0160	-0.0042	-0.5560***	-0.7928***
	(0.0123)	(0.0235)	(0.0452)	(0.0828)	(0.0127)	(0.0243)	(0.0469)	(0.0859)
Market-to-Book	-0.0002	-0.0005	0.0018***	0.0008	-0.0002	-0.0004	0.0015**	0.0006
	(0.0002)	(0.0003)	(0.0006)	(0.0012)	(0.0002)	(0.0003)	(0.0006)	(0.0013)
Cash	0.0202	0.0239	-0.0163	-0.1160	0.0153	0.0252	-0.0426	-0.1827*
	(0.0152)	(0.0277)	(0.0548)	(0.1004)	(0.0158)	(0.0288)	(0.0578)	(0.1050)
A/c Payables	-0.1268***	-0.1742**	-0.4061***	-0.6429***	-0.1260***	-0.1636**	-0.4131***	-0.6531***
	(0.0397)	(0.0724)	(0.1237)	(0.2058)	(0.0427)	(0.0779)	(0.1334)	(0.2250)
A/c Receivables	0.0677**	0.1089*	-0.0430	0.2163	0.0657**	0.1037	-0.0406	0.2296
	(0.0311)	(0.0627)	(0.1063)	(0.1914)	(0.0324)	(0.0654)	(0.1105)	(0.1996)
Tangibility	-0.0482**	-0.0694	-0.0892	-0.0960	-0.0533**	-0.0855*	-0.1086	-0.1743
	(0.0238)	(0.0452)	(0.0932)	(0.1614)	(0.0252)	(0.0473)	(0.0993)	(0.1673)
$VaR_{95\%}$	0.1160***				0.1143***			
	(0.0018)				(0.0019)			
$VaR_{99\%}$		0.1006***				0.0998***		
		(0.0019)				(0.0019)		
$VaR_{95\%,rolling}$			0.1051***				0.1043***	
			(0.0018)				(0.0018)	
$VaR_{99\%,rolling}$				0.1063***				0.1054***
				(0.0017)				(0.0018)
State-level EPU					0.0006***	0.0010***	0.0008***	0.0009***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	159,308	159,308	159,308	159,308	147,251	147,251	147,251	147,251
R-squared	0.8707	0.8742	0.6641	0.6195	0.8709	0.8742	0.6651	0.6172
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7). The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and industry-year fixed effects to control for any firm-level or industry-year level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Robustness – using Russell 3000 as proxy for the market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0041***	0.0067***	0.0057***	0.0083***	0.0033***	0.0051***	0.0042**	0.0063*
	(0.0008)	(0.0013)	(0.0017)	(0.0032)	(0.0008)	(0.0014)	(0.0018)	(0.0034)
Size	-0.0042	0.0068	0.2949***	0.4338***	-0.0042	0.0096	0.2968***	0.4307***
	(0.0035)	(0.0063)	(0.0144)	(0.0259)	(0.0037)	(0.0065)	(0.0150)	(0.0272)
ROA	0.1379***	0.0420	0.4786***	0.5540***	0.1689***	0.0955	0.5064***	0.5672***
	(0.0353)	(0.0598)	(0.0876)	(0.1604)	(0.0370)	(0.0622)	(0.0920)	(0.1678)
Leverage	-0.0044	0.0195	-0.6368***	-0.8728***	-0.0079	0.0013	-0.6504***	-0.8951***
	(0.0136)	(0.0250)	(0.0492)	(0.0867)	(0.0141)	(0.0254)	(0.0509)	(0.0890)
Cash	0.0317*	0.0507*	-0.0305	-0.1211	0.0333**	0.0668**	-0.0444	-0.1575
	(0.0165)	(0.0298)	(0.0574)	(0.1047)	(0.0170)	(0.0306)	(0.0602)	(0.1087)
Market-to-Book	-0.0000	-0.0004	0.0020***	0.0015	-0.0000	-0.0005	0.0016**	0.0009
	(0.0002)	(0.0004)	(0.0007)	(0.0013)	(0.0002)	(0.0004)	(0.0007)	(0.0013)
A/c Payables	-0.1896***	-0.2550***	-0.3787***	-0.6576***	-0.1991***	-0.2546***	-0.3836***	-0.7161***
	(0.0463)	(0.0813)	(0.1219)	(0.2082)	(0.0483)	(0.0844)	(0.1311)	(0.2276)
A/c Receivables	0.1002***	0.1675**	0.1304	0.5467***	0.1071***	0.1726**	0.1538	0.5892***
	(0.0348)	(0.0670)	(0.1119)	(0.1999)	(0.0364)	(0.0701)	(0.1171)	(0.2086)
Tangibility	-0.0973***	-0.1235**	-0.2771***	-0.3297*	-0.0981***	-0.1194**	-0.2606**	-0.3661**
	(0.0260)	(0.0481)	(0.0985)	(0.1694)	(0.0269)	(0.0488)	(0.1038)	(0.1753)
$VaR_{95\%}$	0.1238***				0.1224***			
	(0.0019)				(0.0020)			
$VaR_{99\%}$		0.1057***				0.1051***		
		(0.0020)				(0.0020)		
$VaR_{95\%,rolling}$			0.1065***				0.1055***	
			(0.0018)				(0.0019)	
$VaR_{99\%,rolling}$				0.1104***				0.1096***
				(0.0018)				(0.0019)
State-level EPU					0.0006***	0.0010***	0.0008***	0.0008***
					(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	161,713	161,713	161,713	161,713	149,525	149,525	149,525	149,525
R-squared	0.6865	0.6511	0.5327	0.5112	0.6903	0.6567	0.5349	0.5095
Number of Firms	5,445	5,445	5,445	5,445	4,906	4,906	4,906	4,906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7). The dependent variables in each specification are the four systemic risk measures. Systemic risk measures have been estimated using the Russell 3000 as proxy for the market. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Robustness – Excluding banks and utility firms

	(1)	(2)	(3)	(4)
	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0031***	0.0051***	0.0037*	0.0077**
	(0.0008)	(0.0013)	(0.0019)	(0.0035)
Size	-0.0019	0.0102	0.2855***	0.4264***
	(0.0035)	(0.0066)	(0.0150)	(0.0275)
ROA	0.1415***	0.0532	0.4694***	0.5205***
	(0.0338)	(0.0580)	(0.0882)	(0.1615)
Leverage	-0.0107	0.0075	-0.6005***	-0.8511***
	(0.0131)	(0.0250)	(0.0496)	(0.0881)
Market-to-Book	-0.0001	-0.0004	0.0015**	0.0008
	(0.0002)	(0.0004)	(0.0006)	(0.0013)
Cash	0.0278*	0.0522*	-0.0539	-0.1978*
	(0.0158)	(0.0298)	(0.0605)	(0.1078)
A/c Payables	-0.0314	-0.0074	-0.3464**	-0.5824**
	(0.0425)	(0.0782)	(0.1436)	(0.2424)
A/c Receivables	0.0360	0.0227	0.0029	0.3320
	(0.0352)	(0.0690)	(0.1271)	(0.2260)
Tangibility	-0.0664***	-0.0784*	-0.2030*	-0.2571
	(0.0255)	(0.0476)	(0.1051)	(0.1747)
$VaR_{95\%}$	0.1120***			
	(0.0019)			
$VaR_{99\%}$		0.0980***		
		(0.0020)		
$VaR_{95\%,rolling}$			0.1011***	
			(0.0019)	
$VaR_{99\%,rolling}$				0.1032***
				(0.0019)
State-level EPU	0.0004***	0.0008***	0.0007***	0.0008***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	133,060	133,060	133,060	133,060
R-squared	0.6854	0.6574	0.5276	0.5008
Number of Firms	4,428	4,428	4,428	4,428
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (7) excluding banks and utility firms. The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Propensity Score Matching

Panel A: Matching Diagnostics

A1. Logit Model			A2. T-test for difference of means		
	Pre-Match	Post-Match	Treated	Control	Difference (p-value)
	Treatment Dummy	Treatment Dummy			
Size	0.0854** (0.0416)	-0.0187 (0.0266)	6.7914	6.7817	0.0096 (0.6513)
ROA	-1.1961*** (0.2847)	0.2518 (0.2602)	-0.0068	-0.0077	0.0009 (0.1548)
Leverage	-0.3958*** (0.1313)	0.0129 (0.0954)	0.2544	0.2563	-0.0019 (0.4499)
Market-to-Book	-0.0028 (0.0020)	0.0015 (0.0020)	3.1784	3.1279	0.0504 (0.4697)
Cash	0.3043* (0.1655)	0.0084 (0.1305)	0.2106	0.2103	0.0003 (0.9063)
A/c Payables	0.2281 (0.4087)	0.2360 (0.3126)	0.0739	0.0731	0.0007 (0.4170)
A/c Receivables	-0.3473 (0.3553)	-0.0895 (0.2693)	0.1362	0.1357	0.0005 (0.6784)
Tangibility	0.3093 (0.2629)	0.0412 (0.1909)	0.2323	0.2318	0.0005 (0.8234)
Obs.	63651	32641			
Firm Dummies	Yes	Yes			
Year FE	Yes	Yes			

Panel B: Regression on Matched Sample

	(1)	(2)	(3)	(4)
	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0032*** (0.0010)	0.0050*** (0.0016)	0.0051*** (0.0024)	0.0092** (0.0044)
Size	0.0021 (0.0054)	0.0151 (0.0097)	0.2903*** (0.0208)	0.4077*** (0.0389)
ROA	0.1336** (0.0682)	0.0846 (0.1166)	0.1748 (0.1552)	0.2614 (0.2753)
Leverage	0.0274 (0.0196)	0.0890** (0.0384)	-0.5436*** (0.0670)	-0.8592*** (0.1264)
Market-to-Book	-0.0001 (0.0002)	-0.0003 (0.0006)	0.0034*** (0.0010)	0.0043* (0.0022)
Cash	0.0858*** (0.0245)	0.1254*** (0.0450)	-0.0010 (0.0802)	-0.2550 (0.1611)
A/c Payables	-0.0800 (0.0619)	-0.2360** (0.1217)	-0.2762 (0.1891)	-0.8030** (0.3573)
A/c Receivables	0.0932 (0.0585)	0.1424 (0.1037)	0.1260 (0.1730)	0.5219 (0.3199)
Tangibility	-0.0383 (0.0401)	-0.0306 (0.0772)	-0.2522* (0.1352)	-0.3562 (0.2403)
$VaR_{95\%}$	0.1165*** (0.0029)			
$VaR_{99\%}$		0.0991*** (0.0028)		
$VaR_{95\%,rolling}$			0.0980*** (0.0027)	
$VaR_{99\%,rolling}$				0.1050*** (0.0027)
Obs.	32990	32990	32990	32990
No. of Firms	3460	3460	3460	3460
R-Squared	0.6993	0.6547	0.5282	0.5095
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: This table presents results from propensity score matching analysis. Panel A shows diagnostics from the matching process. Regression estimates from the matched sample are presented in Panel B. Firm-specific variables have been winsorized at 1% and 99% to mitigate the effect of outliers. Figures in parentheses are heteroskedasticity-robust standard errors clustered by firm. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 10: IV-2SLS Estimation – State-level Prisk as the Instrument

	(1) Prisk	(2) $\Delta CoVaR_{95\%}$	(3) Prisk	(4) $\Delta CoVaR_{99\%}$	(5) Prisk	(6) $\Delta CoVaR_{95\%,rolling}$	(7) Prisk	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk_State	0.1142***		0.1167***		0.1159***		0.1186***	
	(0.0163)		(0.0163)		(0.0163)		(0.0162)	
Prisk_Fitted		0.3691***		0.7096***		0.6289***		0.5218***
		(0.0637)		(0.1171)		(0.1238)		(0.1587)
Size	-0.0132	0.0005	-0.0126	0.0169	-0.0110	0.2936***	-0.0106	0.4357***
	(0.0177)	(0.0074)	(0.0177)	(0.0142)	(0.0177)	(0.0183)	(0.0176)	(0.0280)
ROA	-0.5747***	0.3845***	-0.5942***	0.5006***	-0.4768***	0.7861***	-0.4999***	0.7918***
	(0.1353)	(0.0704)	(0.1352)	(0.1301)	(0.1349)	(0.1327)	(0.1356)	(0.1888)
Leverage	-0.0881	0.0278	-0.0848	0.0698	-0.1195**	-0.5519***	-0.1143**	-0.8407***
	(0.0569)	(0.0252)	(0.0570)	(0.0470)	(0.0573)	(0.0614)	(0.0570)	(0.0903)
Cash	0.0771	0.0014	0.0763	0.0089	0.0669	-0.0876	0.0667	-0.2255**
	(0.0709)	(0.0313)	(0.0709)	(0.0596)	(0.0710)	(0.0739)	(0.0709)	(0.1103)
Market-to-Book	-0.0016*	0.0006	-0.0016*	0.0008	-0.0014	0.0026***	-0.0014	0.0016
	(0.0009)	(0.0004)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0014)
A/c Payables	0.0630	-0.2089**	0.0605	-0.2873*	0.0294	-0.3793**	0.0327	-0.6274***
	(0.1762)	(0.0818)	(0.1763)	(0.1528)	(0.1753)	(0.1784)	(0.1754)	(0.2407)
A/c Receivables	-0.1946	0.1813**	-0.1901	0.3111**	-0.1960	0.2738*	-0.1971	0.6237***
	(0.1740)	(0.0721)	(0.1741)	(0.1422)	(0.1736)	(0.1598)	(0.1739)	(0.2298)
Tangibility	0.1297	-0.1393***	0.1347	-0.2005**	0.1174	-0.3125**	0.1235	-0.3911**
	(0.1161)	(0.0516)	(0.1160)	(0.0954)	(0.1159)	(0.1237)	(0.1157)	(0.1788)
$VaR_{95\%}$	0.0087***	0.1121***						
	(0.0016)	(0.0021)						
$VaR_{99\%}$			0.0035***	0.0969***				
			(0.0008)	(0.0021)				
$VaR_{95\%,rolling}$					0.0109***	0.0941***		
					(0.0014)	(0.0025)		
$VaR_{99\%,rolling}$							0.0057***	0.1001***
							(0.0007)	(0.0021)
State-level EPU	0.0011***	0.0001	0.0011***	0.0000	0.0011***	-0.0001	0.0011***	0.0001
	(0.00009)	(0.0001)	(0.00009)	(0.0002)	(0.00009)	(0.0002)	(0.00009)	(0.0002)
Anderson-Rubin Wald F-Statistic	99.73***		116.89***		50.53***		13.78***	
Kleibergen-Paap Wald rk F-Statistic	48.85***		50.86***		50.42***		52.97***	
Observations		149,084		149,084		149,084		149,084
Number of Firms		4,903		4,903		4,903		4,903
Firm FE		Yes		Yes		Yes		Yes
Year FE		Yes		Yes		Yes		Yes

Note: This table presents estimates from IV-2SLS estimation using average state-level Prisk as the instrument. Columns 1,3,5, and 7 are the first stage regressions. In columns 2,4,6 and 8, the fitted Prisk from first-stage regression are the main explanatory variable. All variables are winsorized at 1% and 99% to minimize the effect of outliers. Figures in parentheses are heteroskedasticity-robust standard errors clustered by firm. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 11: IV-2SLS Estimation – Industry-level Prisk as the Instrument

	(1) Prisk	(2) $\Delta CoVaR_{95\%}$	(3) Prisk	(4) $\Delta CoVaR_{99\%}$	(5) Prisk	(6) $\Delta CoVaR_{95\%,rolling}$	(7) Prisk	(8) $\Delta CoVaR_{99\%,rolling}$
Prisk_Industry	0.2364***		0.2385***		0.2361***		0.2392***	
	(0.0170)		(0.0170)		(0.0169)		(0.0169)	
Prisk_Fitted		0.3204***		0.5608***		0.4157***		0.4802***
		(0.0279)		(0.0494)		(0.0513)		(0.0838)
Size	-0.0118	0.0004	-0.0113	0.0159	-0.0100	0.2913***	-0.0095	0.4350***
	(0.0178)	(0.0067)	(0.0178)	(0.0119)	(0.0177)	(0.0163)	(0.0177)	(0.0278)
ROA	-0.5708***	0.3572***	-0.5867***	0.4126***	-0.4754***	0.6918***	-0.4924***	0.7805***
	(0.1351)	(0.0574)	(0.1349)	(0.0988)	(0.1346)	(0.1042)	(0.1354)	(0.1700)
Leverage	-0.0760	0.0242	-0.0733	0.0590	-0.1058*	-0.5735***	-0.1021*	-0.8393***
	(0.0569)	(0.0226)	(0.0570)	(0.0397)	(0.0573)	(0.0540)	(0.0570)	(0.0884)
Cash	0.0748	0.0063	0.0742	0.0223	0.0657	-0.0705	0.0653	-0.2249**
	(0.0709)	(0.0280)	(0.0709)	(0.0499)	(0.0709)	(0.0655)	(0.0708)	(0.1089)
Market-to-Book	-0.0016*	0.0005	-0.0016*	0.0006	-0.0014	0.0022***	-0.0014	0.0015
	(0.0009)	(0.0003)	(0.0009)	(0.0006)	(0.0009)	(0.0007)	(0.0009)	(0.0014)
A/c Payables	0.0698	-0.2072***	0.0676	-0.2814**	0.0386	-0.3768**	0.0406	-0.6237***
	(0.1763)	(0.0750)	(0.1763)	(0.1316)	(0.1754)	(0.1554)	(0.1755)	(0.2378)
A/c Receivables	-0.1850	0.1731***	-0.1811	0.2852**	-0.1870	0.2363*	-0.1884	0.6272***
	(0.1736)	(0.0644)	(0.1737)	(0.1197)	(0.1733)	(0.1357)	(0.1736)	(0.2256)
Tangibility	0.1540	-0.1355***	0.1583	-0.1869**	0.1422	-0.2860***	0.1476	-0.4002**
	(0.1159)	(0.0462)	(0.1159)	(0.0796)	(0.1158)	(0.1101)	(0.1156)	(0.1760)
$VaR_{95\%}$	0.0074***	0.1126***						
	(0.0016)	(0.0020)						
$VaR_{99\%}$			0.0030***	0.0976***				
			(0.0008)	(0.0020)				
$VaR_{95\%,rolling}$					0.0101***	0.0965***		
					(0.0013)	(0.0020)		
$VaR_{99\%,rolling}$							0.0054***	0.1004***
							(0.0007)	(0.0019)
State-level EPU	0.0010***	0.0001**	0.0010***	0.0002**	0.0010***	0.0002**	0.0010***	0.0002
	(0.00009)	(0.0001)	(0.00009)	(0.0001)	(0.0009)	(0.0001)	(0.00009)	(0.0002)
Anderson-Rubin Wald F-Statistic	293.93***		279.03***		94.11***		39.03***	
Kleibergen-Paap Wald rk F-Statistic	192.75***		196.71***		193.50***		198.96***	
Observations		149,466		149,466		149,466		149,466
Number of Firms		4,905		4,905		4,905		4,905
Firm FE		Yes		Yes		Yes		Yes
Year FE		Yes		Yes		Yes		Yes

Note: This table presents estimates from IV-2SLS estimation using average industry-level Prisk as the instrument. Columns 1,3,5, and 7 are the first stage regressions. In columns 2,4,6 and 8, the fitted Prisk from first-stage regression are the main explanatory variable. All variables are winsorized at 1% and 99% to minimize the effect of outliers. Figures in parentheses are heteroskedasticity-robust standard errors clustered by firm. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 12: Description of Board Interlock Networks

Panel A

	Summary Statistics					Pearson Correlation		
	N	Mean	SD	25th Percentile	75th Percentile	Degree	Eigenvector	Betweenness
Degree	161,713	4.32	4.41	1.00	6.00	1		
Eigenvector	161,713	0.0430	0.0884	0.0002	0.0449	0.8066***	1	
Betweenness	161,713	0.0003	0.0006	0.0000	0.0004	0.8620***	0.7891***	1

Panel B

	Quartile of Prisk								
	1		2		3		4		Difference (1-4)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Degree	3.95	4.01	4.38	4.32	4.45	4.48	4.48	4.76	-0.5348***
Eigenvector	0.0366	0.0748	0.0428	0.0848	0.0445	0.0905	0.0479	0.1011	-0.0113***
Betweenness	0.0003	0.0005	0.0003	0.0005	0.0003	0.0006	0.0003	0.0007	-0.00007***

Note: This table describes the board network centrality measures. Panel A presents summary statistics and pairwise correlations. In Panel B, summary statistics for centrality measures are categorized by quartiles of Prisk. The Difference column gives the difference in mean centrality between firms in the lowest (1) and highest (4) quartiles. *, **, and *** indicates statistical significance at 10%, 5%, and 1% respectively.

Table 13: Board Network Regressions

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%}$	(4) $\Delta CoVaR_{99\%}$	(5) $\Delta CoVaR_{95\%}$	(6) $\Delta CoVaR_{99\%}$
Prisk	0.0031***	0.0051***	0.0031***	0.0052***	0.0031***	0.0052***
	(0.0008)	(0.0013)	(0.0008)	(0.0013)	(0.0008)	(0.0013)
Degree	0.0013	0.0023				
	(0.0034)	(0.0067)				
Prisk × Degree	0.0040***	0.0064***				
	(0.0010)	(0.0018)				
Eigenvector			0.0085***	0.0158**		
			(0.0033)	(0.0063)		
Prisk × Eigenvector			0.0037***	0.0059***		
			(0.0012)	(0.0021)		
Betweenness					0.0028	0.0045
					(0.0030)	(0.0055)
Prisk × Betweenness					0.0030***	0.0053**
					(0.0011)	(0.0021)
Size	-0.0050	0.0072	-0.0057	0.0058	-0.0050	0.0071
	(0.0036)	(0.0066)	(0.0036)	(0.0065)	(0.0036)	(0.0065)
ROA	0.1756***	0.0828	0.1764***	0.0843	0.1760***	0.0834
	(0.0350)	(0.0594)	(0.0350)	(0.0592)	(0.0351)	(0.0593)
Leverage	-0.0034	0.0124	-0.0037	0.0118	-0.0035	0.0122
	(0.0134)	(0.0252)	(0.0134)	(0.0252)	(0.0134)	(0.0252)
Cash	0.0309*	0.0658**	0.0310*	0.0660**	0.0310*	0.0661**
	(0.0163)	(0.0300)	(0.0163)	(0.0300)	(0.0163)	(0.0300)
Market-to-Book	-0.0000	-0.0004	-0.0000	-0.0004	-0.0000	-0.0004
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
A/c Payables	-0.1840***	-0.2426***	-0.1835***	-0.2417***	-0.1839***	-0.2423***
	(0.0467)	(0.0813)	(0.0466)	(0.0812)	(0.0467)	(0.0813)
A/c Receivables	0.1121***	0.1818***	0.1098***	0.1778**	0.1109***	0.1800***
	(0.0348)	(0.0698)	(0.0346)	(0.0696)	(0.0347)	(0.0696)
Tangibility	-0.0941***	-0.1102**	-0.0937***	-0.1098**	-0.0936***	-0.1094**
	(0.0257)	(0.0467)	(0.0257)	(0.0467)	(0.0257)	(0.0466)
$VaR_{95\%}$	0.1157***		0.1157***		0.1157***	
	(0.0020)		(0.0020)		(0.0020)	
$VaR_{99\%}$		0.0997***		0.0997***		0.0997***
		(0.0020)		(0.0020)		(0.0020)
State-level EPU	0.0005***	0.0009***	0.0005***	0.0009***	0.0005***	0.0009***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Observations	149,525	149,525	149,525	149,525	149,525	149,525
R-squared	0.6838	0.6469	0.6839	0.6470	0.6838	0.6469
Number of Firms	4,906	4,906	4,906	4,906	4,906	4,906
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents estimates of OLS regressions of the form in eq. (8). The dependent variables in each specification are the four systemic risk measures. Continuous firm-level variables have been winsorized at the 1% and 99% levels to minimize the impact of outliers. All specifications include firm and year-fixed effects to control for any firm-level or year-level unobserved heterogeneity. Figures in parentheses indicate heteroskedasticity-robust standard errors, clustered at firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Description of Lobbying Data

Panel A

	Summary Statistics				
	N	Mean	SD	25th Percentile	75th Percentile
Lobbying	161,713	0.2835	0.4507	0	1
Lobby Exp.	161,713	3.2705	5.2582	0	9.9035
No. of Issues	161,713	1.2914	2.9938	0	1
Degree	161,713	99.692	187.07	0	116
Eigenvector	161,713	0.1521	0.2817	0	0.1723

Panel B

	Quartile of Prisk								
	1		2		3		4		Difference (1-4)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Lobby Exp	2.6157	4.8239	3.1669	5.1788	3.4128	5.3316	3.8873	5.5895	-1.2715***
No. of Issues	0.9920	2.6292	1.2524	2.9803	1.3644	3.0821	1.5569	3.2234	-0.5649***
Degree	78.6239	168.4477	96.46	184.50	104.65	191.22	119.05	200.41	-40.4281***
Eigenvector	0.1205	0.2549	0.1474	0.2780	0.1596	0.2876	0.1806	0.3008	-0.0601***

Note: This table describes the lobbying data. Panel A presents summary statistics. In Panel B, summary statistics for centrality measures are categorized by quartiles of Prisk. The Difference column gives the difference in mean centrality between firms in the lowest (1) and highest (4) quartiles. *, **, and *** indicates statistical significance at 10%, 5%, and 1% respectively.

Table 15: Effect of Corporate Lobbying

Panel A: Lobbying Activity

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%}$	(4) $\Delta CoVaR_{99\%}$
PRisk	0.0019*	0.0028	0.0016	0.0023
	(0.0010)	(0.0018)	(0.0010)	(0.0018)
Lagged Lobbying	-0.0063	-0.0047		
	(0.0060)	(0.0112)		
Prisk × Lagged Lobbying	0.0032*	0.0065**		
	(0.0016)	(0.0029)		
Lagged Ln(1+Lobby_Exp)			-0.0007	-0.0006
			(0.0006)	(0.0010)
Prisk × Lagged Ln(1+Lobby_Exp)			0.0003**	0.0007***
			(0.0001)	(0.0003)
Obs.	1,40,602	1,40,602	1,40,602	1,40,602
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Lobbying Issues

	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0016*	0.0026	0.0014	0.0057
	(0.0009)	(0.0016)	(0.0021)	(0.0038)
No. of Issues (lagged)	-0.0007	-0.0003	0.0010	-0.0041
	(0.0011)	(0.0019)	(0.0038)	(0.0061)
Prisk × No. of Issues (lagged)	0.0008***	0.0016***	0.0015**	0.0003
	(0.0003)	(0.0005)	(0.0006)	(0.0010)
Obs.	1,40,602	1,40,602	1,40,602	1,40,602
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel C: Lobby Networks

	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0026***	0.0043***	0.0026***	0.0043***	0.0032*	0.0061*	0.0032*	0.0060*
	(0.0008)	(0.0014)	(0.0008)	(0.0014)	(0.0019)	(0.0034)	(0.0019)	(0.0034)
Degree	-0.0031	-0.0037			0.0127	-0.0038		
	(0.0033)	(0.0059)			(0.0108)	(0.0186)		
Prisk × Degree	0.0023***	0.0048***			0.0038**	0.0001		
	(0.0008)	(0.0014)			(0.0018)	(0.0030)		
Eigenvector			-0.0034	-0.0036			0.0110	-0.0035
			(0.0032)	(0.0059)			(0.0103)	(0.0181)
Prisk × Eigenvector			0.0022***	0.0049***			0.0038**	0.0004
			(0.0008)	(0.0014)			(0.0018)	(0.0030)
Obs.	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents estimates from OLS regressions of the form in eq. (9) using lobbying data. Network variables are standardized within each quarter to ensure comparability. Continuous firm-level variables are winsorized at 1% and 99% to minimize the effect of outliers. All specifications include firm and year fixed effects to control for unobserved heterogeneity. Figures in parentheses are heteroskedasticity-robust standard errors clustered by firm. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 16: Description of Political Contributions Data

Panel A

	Summary Statistics				
	N	Mean	SD	25th Percentile	75th Percentile
PAC Contributor	161,713	0.1730	0.3783	0	0
Contribution	161,713	1.6192	3.5927	0	0
Degree	161,713	24.5645	68.631	0	0
Eigenvector	161,713	0.0775	0.2053	0	0

Panel B

	Quartile of Prisk								
	1		2		3		4		Difference (1-4)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
PAC Contributor	0.1324	0.3389	0.1659	0.3720	0.1828	0.3865	0.2110	0.4080	-0.0786***
Contribution	1.2108	3.1452	1.5392	3.5002	1.7176	3.6853	2.0099	3.9464	-0.7991***
Degree	16.981	56.667	22.546	64.724	26.347	70.858	32.392	79.346	-15.411***
Eigenvector	0.0541	0.1705	0.0717	0.1952	0.0832	0.2121	0.1012	0.2351	-0.0471***

Note: This table describes the corporate PACs political contributions data. PAC Contributor is a dummy indicating whether a firm's PAC makes a positive contribution to federal candidates. Contribution is the natural logarithm of 1 plus actual PAC contribution made. Panel A presents summary statistics. In Panel B, summary statistics for centrality measures are categorized by quartiles of Prisk. The Difference column gives the difference in mean centrality between firms in the lowest (1) and highest (4) quartiles. *, **, and *** indicates statistical significance at 10%, 5%, and 1% respectively.

Table 17: Effect of PAC Contributions

Panel A: PAC federal contributions

	(1) $\Delta CoVaR_{95\%}$	(2) $\Delta CoVaR_{99\%}$	(3) $\Delta CoVaR_{95\%}$	(4) $\Delta CoVaR_{99\%}$
PRisk	0.0013	0.0020	0.0012	0.0019
	(0.0009)	(0.0016)	(0.0009)	(0.0016)
Lagged Contributor	-0.0022	-0.0087		
	(0.0060)	(0.0112)		
Prisk × Lagged Contributor	0.0074**	0.0133***		
	(0.0019)	(0.0034)		
Lagged Ln(1+PAC_Exp)			-0.0000	-0.0006
			(0.0007)	(0.0013)
Prisk × Lagged Ln(1+PAC_Exp)			0.0008***	0.0015***
			(0.0002)	(0.0004)
Obs.	140,602	140,602	140,602	140,602
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

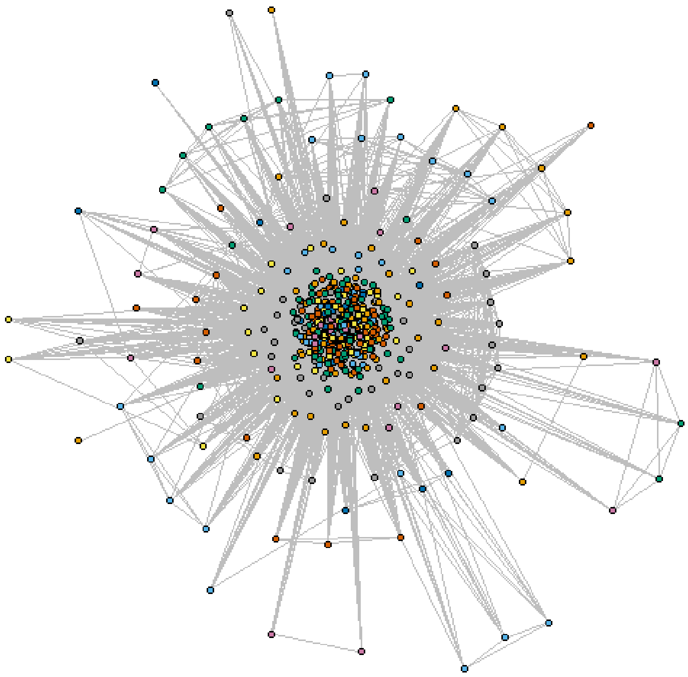
Panel B: Political Contribution Networks

	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%}$	$\Delta CoVaR_{99\%}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$	$\Delta CoVaR_{95\%,rolling}$	$\Delta CoVaR_{99\%,rolling}$
Prisk	0.0025***	0.0043***	0.0025***	0.0042***	0.0033*	0.0057*	0.0033*	0.0057*
	(0.0008)	(0.0014)	(0.0008)	(0.0014)	(0.0018)	(0.0034)	(0.0018)	(0.0034)
Degree	-0.0013	-0.0065			0.0266***	0.0387***		
	(0.0028)	(0.0051)			(0.0077)	(0.0141)		
Prisk × Degree	0.0029***	0.0052***			0.0033**	0.0018		
	(0.0008)	(0.0015)			(0.0016)	(0.0026)		
Eigenvector			-0.0020	-0.0076			0.0247***	0.0377***
			(0.0027)	(0.0050)			(0.0078)	(0.0141)
Prisk × Eigenvector			0.0030***	0.0054***			0.0034**	0.0019
			(0.0008)	(0.0014)			(0.0016)	(0.0027)
Obs.	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602	1,40,602
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents estimates from OLS regressions of the form in eq. (10) using PAC federal contributions data. Contributor is an indicator variable for whether a firm's PAC donated to federal candidates. PAC_Exp is the natural logarithm of 1 plus PAC contributions. Network variables are standardized within each quarter to ensure comparability. Continuous firm-level variables are winsorized at 1% and 99% to minimize the effect of outliers. All specifications include firm and year fixed effects to control for unobserved heterogeneity. Figures in parentheses are heteroskedasticity-robust standard errors clustered by firm. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively

Figure 1: Lobbying Networks in 2012 Q4

Panel A: All lobbying firms



Panel B: Industry-wise Top Firms (By Total Assets)

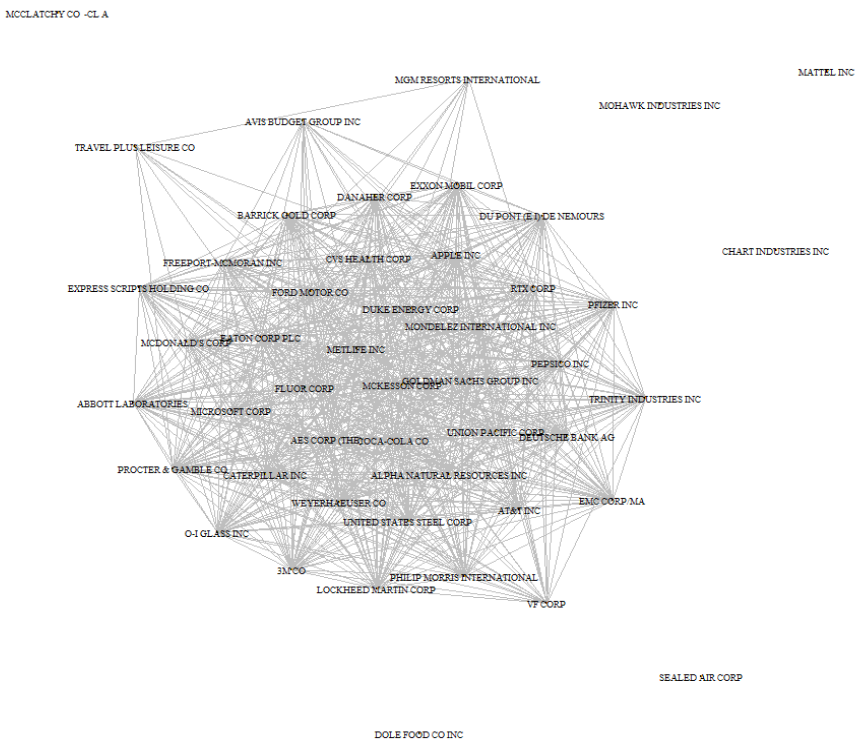
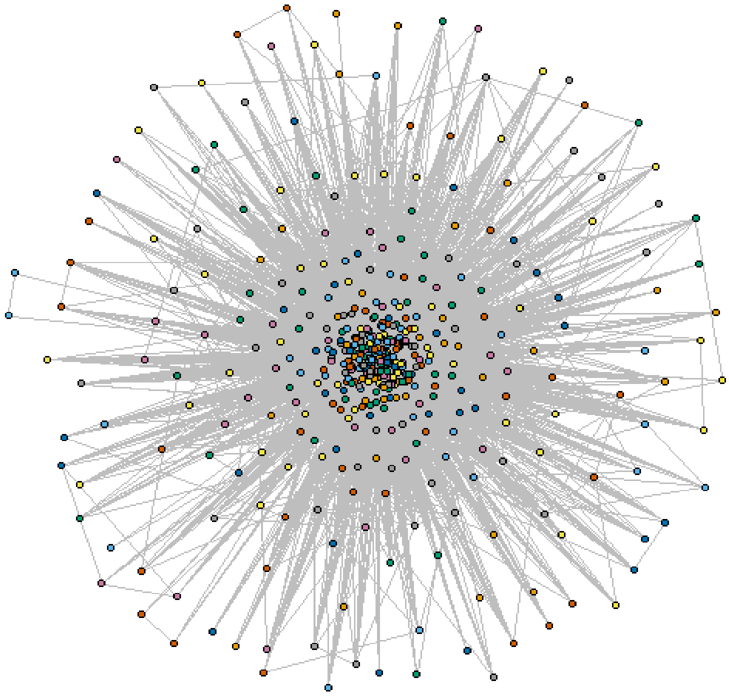


Figure 2: PAC Networks in 2012 Q4

Panel A: All contributing PACs



Panel B: Industry-wise Top PACs (By Total Assets)